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Optimization Strategies for Pump-hydro Storage and Wind Farm Coordination Including Wind Power Uncertainty

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Abstract

Several countries, such as Portugal and Spain, have a significant installed capacity of large-scale reversible hydro power plants with reservoir (pump-hydro storage – PHS) in its portfolio. For instance, in Portugal, installed PHS capacity is 983 MW, corresponding to 22% of the wind and solar power capacity and 5.1% of the total generation capacity.

The PHS flexibility can be combined with wind farms in order to smooth wind power variations and hedge risk associated to generation uncertainty. In this dissertation, a new stochastic optimization model for optimizing the coordination between a wind farm and a PHS unit, which participates in the day-ahead electrical energy market, is described. The proposed optimization problem has the following innovative characteristics compared to the state of the art: (a) the wind power uncertainty is modelled through a set of scenarios that capture the temporal dependency of forecast errors (i.e., decision variables that satisfy all constraints in all scenarios are determined); (b) different attitudes of the decision-maker towards risk are modelled with utility theory concepts (i.e., expected utility maximization, in contrast to the expected value paradigm). The objective function includes costs associated to imbalances, spilled wind power, as well as profit from price arbitrage.

After the day-ahead optimization, and during the operating day, it is necessary to operate the wind-PHS system in order to minimize the deviation between accepted bids and actual energy delivered. This is accomplished by designing a constrained optimization problem that, based on updated wind power forecasts, minimizes the absolute deviation between bids and actual generation values. This second problem is a novelty in the state of the art and enables an effective calculation of the total profit associated to the market participation.

The results, for real wind power generation data and PHS unit, show that the stochastic model achieves a marginally higher total profit compared to a deterministic model (i.e., uses wind power point forecasts as input). The impact of different decision-makers risk profiles is also evaluated.

Resumo

Vários países, como Portugal e Espanha, contêm, no seu portfólio, uma grande capacidade instalada de aproveitamentos hídricos com armazenamento e possibilidade de bombagem (grupos reversíveis), denominados na literatura anglo-saxónica por: Pump-Hydro Storage – PHS. Por exemplo, em Portugal, a capacidade instalada de PHS é de 983 MW, correspondendo a 22% da potência solar e eólica instalada e 5.1% de toda a capacidade instalada.

A flexibilidade do PHS pode ser combinada com um parque eólico de forma a suavizar as variações da potência eólica e reduzir o risco associado à incerteza da sua produção. Nesta dissertação, é descrito um novo modelo de otimização estocástica para a coordenação entre um parque eólico e uma unidade PHS, com participação no mercado diário de energia elétrica. A otimização proposta apresenta as seguintes características inovadoras relativamente ao estado da arte: (a) a incerteza associada à potência eólica é modelizada através de um conjunto de cenários que captam a dependência temporal dos erros de previsão (i.e., são determinadas variáveis de decisão que satisfazem todas as restrições em todos os cenários); (b) diferentes atitudes do agente de decisão em relação ao risco são modelizadas recorrendo a conceitos de função utilidade (i.e., maximização da utilidade esperada contrastando com o paradigma do valor esperado). A função objetivo inclui custos associados com desvios na geração, desperdício de energia renovável, assim como lucro proveniente da arbitragem.

Depois da otimização do dia seguinte, e durante o dia de operação, é necessário operar o sistema parque eólico-PHS de forma a minimizar os desvios entre as propostas aceites em mercado e a verdadeira energia entregue à rede. Isto é efetuado através da criação de um problema de otimização que, com base em previsões eólicas atualizadas, minimiza o desvio absoluto entre a energia ofertada em mercado e os valores reais de produção. Este segundo problema de otimização representa uma novidade em relação ao estado da arte e permite um cálculo preciso do lucro total associado à participação em mercado.

Os resultados, considerando dados reais de vento e da unidade PHS, mostram que o modelo estocástico alcança um ligeiro aumento de lucro comparativamente com o modelo determinístico (i.e., usando *point forecasting* como método de previsão eólica). O impacto dos diferentes perfis dos agentes de decisão são também estudados.

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Finally, I would like to thank my girlfriend, Diana, who was always there cheering me up and stood by me through the good times and bad.

Jorge Filipe

"The science of today is the technology of tomorrow"

Edward Teller

Contents

List of Figures

List of Tables

Abbreviations and Symbols

Abbreviations List

CVaR	Conditional Value at Risk
DA	Day-ahead (Market and Strategy)
DM	Decision Maker
ELSPOT	Nord Pool Spot's day ahead prices
ERCOT	Electric Reliability Council of Texas
EU	European Union
EV	Expected Value
ID	Intra-day (Market)
KDE	Kernel Density Estimators
MIBEL	Iberian Electrical Energy Market
NPRI	Normalized Prediction Risk Index
NREL	National Renewable Energy Laboratory
NWP	Numerical Weather Predictions
OS	Operational Management Strategy
PF	Point Forecast
PHS	Pump-Hydro Storage
SCADA	Supervisory Control and Data Acquisition
VPP	Virtual Power Plant
WP	Wind Power
WPF	Wind Power Forecast

Symbols List

c_{hydro}	costs associated with hydroelectric generation
c_{pump}	costs associated with the pump-unit operation
$d_{s,i}$	wind power imbalance for scenario s at period i
$E_{s,i}$	energy stored in the reservoir for scenario s at the beginning of period i
E^M	maximum storage capacity of the water reservoir
E^{begin}	amount of energy stored in the reservoir at the beginning of the optimization period
E^{end}	amount of energy stored in the reservoir at the end of the optimization period
i	period index (hour)
L^{max}	maximum system profit
L^{min}	minimum system profit
n	number of hours of the day
p_i	spot market price at period i
p_i^+	positive imbalance price paid for generating more than the contracted power at interval i
p_i^-	negative imbalance price paid for generating less than the contracted power at interval i
p_{max}^+	maximum positive imbalance price
p_{max}^-	maximum negative imbalance price
$P_{DLs,i}$	amount of wind power wasted in the dumping loads for scenario s at period i
P_{Gi}	wind power directly delivered to the grid at interval i
P_G^M	nominal power of the wind farm
P_{Hi}	hydroelectric power generated at interval i
P_H^M	maximum generation capacity of the hydro turbines
$P_{Ps,i}$	pump-unit power at interval i
P_P^M	maximum pumping capacity of the pump-unit
$P_{Ws,i}$	wind power available for scenario s at interval i
W^{max}	maximum boundary for the parcel of the multi-attribute utility function that accounts the wasting of renewable energy
W^{min}	minimum boundary for the parcel of the multi-attribute utility function that accounts the wasting of renewable energy
s	scenario index

S	number of wind power scenarios considered
t	amount of time that pumping/generation operation takes to be carried out in each simulation time interval i
$T_{s,i}$	regulation costs for scenarios s and period i
β	risk tolerance considered in the utility function
η_H	efficiency of hydro generation
η_P	efficiency of pumping generation
k_1,k_2	parameters associated with the multi-attribute utility function
ρ_s	probability of scenario s
γ	performance coefficient used to compare the stochastic and deterministic methods

Chapter 1

Introduction

1.1 General Context and Motivation

The future electricity system will face various challenges originating from both supply and demand side. Just a decade ago the electrical power system used to be completely dependent on conventional fossil-fuelled power plants. The increasing concern over the environmental impact and sustainability of those conventional sources of electric energy and the ongoing political and economic instability present in the major petroleum producing countries has led to the implementation of ambitious targets for renewable power generation.

Each year, less than 10% of the greenhouse gases emitted worldwide come from within the European Union [1]. The EU's share of global emissions is falling as Europe reduces its own emissions, but other parts of the world, especially the major emerging economies (i.e. China and India) continue to grow.

Due to measures implemented at European level as well by individual countries at national scale, the EU is on track to achieve its targets for cutting greenhouse gas emissions established for 2020. Figure 1.1 depicts the decrease in greenhouse emission from 1990 until nowadays, obtained from the *Annual European Union greenhouse gas inventory* [2]. Until 2020 the European Union aims to achieve a 20% reduction in greenhouse emissions over the amount issued in 1990.

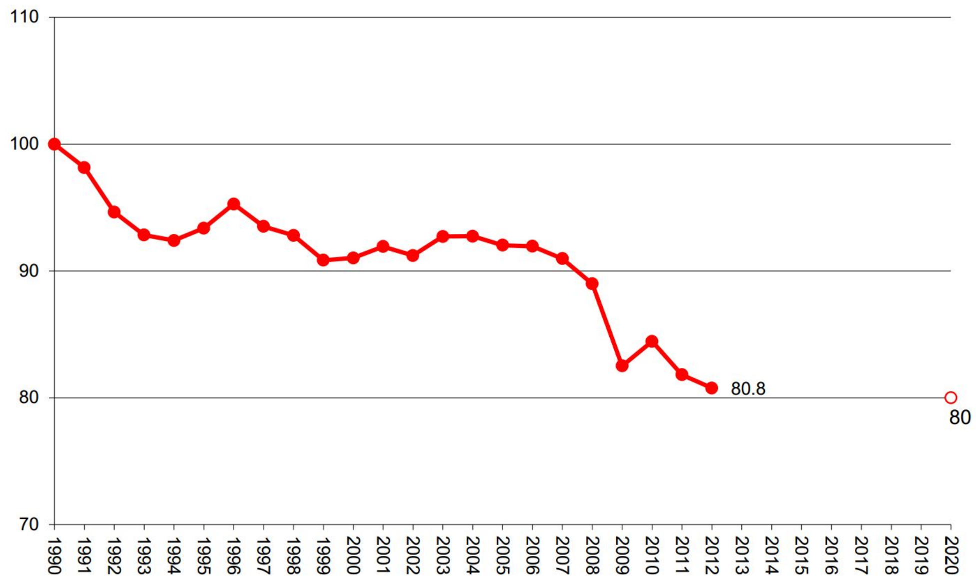

Figure 1.1: Greenhouse emissions from 1990-2012

Despite the considerable decrease in the emissions in the past decade and although there is only a 0.8% gap between current level and target to be achieved in 8 years, the report discloses that the CO_2 emissions from electricity generation have increased. The quote presented bellow shows an increase of 3% (26 million tonnes) from 2011 to 2012, and identifies the causes.

> ***CO_2 from public electricity and heat production****: + 26 million tonnes or + 3 %*
>
> *Increasing emissions occurred in particular in Germany, the United Kingdom and Spain. In Germany, power production from coal increased mainly due to lower nuclear power production as well as higher exports and lower imports of electricity. In the United Kingdom there was a substantial increase in the use of coal for power generation. In Spain, the main reasons are a decline in hydropower production and a considerable shift from natural gas to coal use in public power production.*

One can conclude that despite the favourable global results, the electric generation sector has margin to improve and contribute to the minimization of carbon emissions. The obvious solution is to invest in the research and development of renewable and sustainable sources of energy.

Research and development of wind power generation enabled this technology to reach a level of maturity that allowed the large-scale implementation of wind farms and its operation in liberalized electricity markets. Figure 1.2 shows the global cumulative wind power capacity, one can verify that for the past decade the wind power installed capacity has increased from 50 GW to almost 350 GW, contributing significantly for the decarbonization of the system.

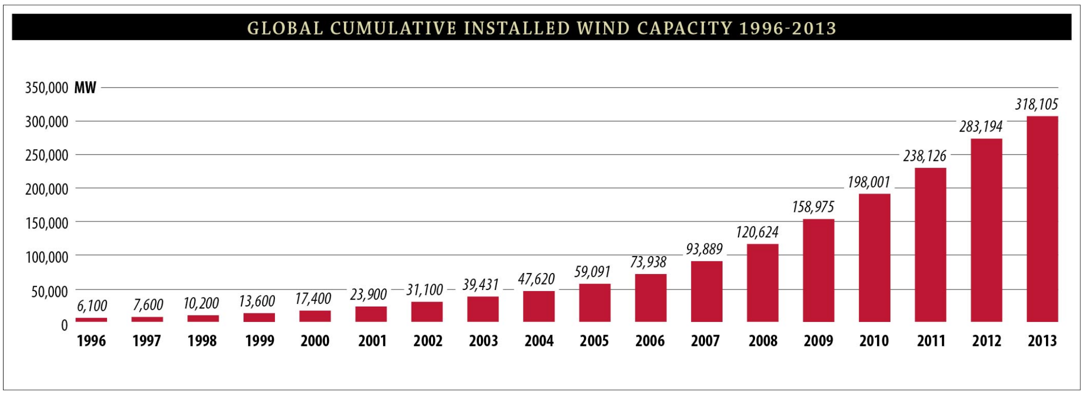

Figure 1.2: Global cumulative installed wind capacity 1996-2013 [3]

The variability of wind speed and direction is one of the main drawbacks of this technology, since this volatility makes it difficult to forecast the output power of a wind farm, even for a few hours ahead. On behalf of the transmission system operator, this adds a concern, since results in differences between contracted and real generated power. This power imbalances are penalized following a regulatory system, in which the wind farm's operator has to pay a fee for the surplus or deficit of wind power delivered.

To smooth wind power variations and hedge risk associated to generation uncertainty, the wind farm can be combined with a reversible hydro power plant with reservoir (pump-hydro storage – PHS). As a result, when there are surplus of wind power the pump unit stores water in the reservoir that can be generated when a power deficit arises. Additionally, the PHS adds the possibility of price arbitrage, where water is pumped into the reservoir at lower prices to be generated at more profitable periods.

The European Union believes that energy storage will play a key role in enabling the development of a low-carbon electricity system. Energy storage can supply more flexibility and balancing to the grid, providing a back-up to intermittent renewable energy. Locally, it can improve the management of distribution networks, reducing costs and improving efficiency. In this way, it can ease the market introduction of renewable, accelerate the decarbonisation of the electricity grid, improve the security and efficiency of electricity transmission and distribution [4].

Energy storage is already an established technology, with PHS for large-scale electricity storage representing almost 99% of current world wide storage capacity.

Several countries, such as Portugal and Spain, have a significant installed capacity of PHS in its portfolio. For instance, in Portugal, installed PHS capacity was 983 MW, corresponding to 22% of the wind and solar power capacity and 5.1% of the total generation capacity.

This dissertation presents a new stochastic optimization model for optimizing the coordination between a wind farm and a PHS unit, which participates in the day-ahead electricity energy market. To account for the wind power uncertainty, wind power short-term scenarios that capture the temporal dependency of forecast errors are used. The optimization comprehends the attitude of the decision maker towards risk and its attitude towards the wasting of renewable energy.

It is also presented a new operational management strategy, which performs during the operating day and uses updated wind power forecasts to define new operation points for every hour, aiming to minimize power imbalances.

1.2 Objectives and Contributions

This dissertation presents two strategies that aim to optimize the coordination between a reversible hydro power plant and a wind farm: stochastic day-ahead strategy and operational management strategy.

The day-ahead optimization problem defines the day-ahead bids proposed to the electrical energy market and has the following innovative characteristics compared with the state of the art:

- The use of short-term wind power scenarios that capture the temporal dependency of forecast errors to model wind power uncertainty. This results in a set of global and scenario-dependent variables, that are mutually dependent and all have to comply with the system's constraints.

- Different attitudes of the decision-maker towards risk are modelled with concepts from utility theory (i.e., expected utility maximization, in contrast to the expected value paradigm). In consequence, two utility functions are used, one (unidimensional) accounting the decision maker attitude towards risk and the other (multi-attribute) accounting the wasting of renewable energy. The objective functions include costs associated to imbalances, spilled wind power, as well as profit from price arbitrage.

After the day-ahead optimization, and during the operating day, it is necessary to operate the wind farm and PHS system in order to minimize the deviation between accepted bids and actual energy delivered. The operational management strategy is a novelty in the state of the art and consists in a constrained optimization problem that, based on updated wind power forecasts, minimizes the absolute deviation between bids and actual generation values. This strategy enables an effective calculation of the total profit associated to the market participation.

1.3 Structure

This dissertation is constituted by five chapters.

The present chapter discloses the context and motivation behind the development of the dissertation, as well as the objectives and contributions made.

Chapter 2 provides a review of the state of the art. It stars by describing the organization and operation of the electrical energy market, followed by a characterization of several methods of wind power forecasting. From Section 2.3 to Section 2.5.2 several optimization strategies are reviewed comprehending: hydropower plants bidding strategies, wind farm bidding strategies, deterministic and stochastic wind-hydro coordination. The last section of the chapter provides a comparison between all works reviewed and this dissertation.

Chapter 3 features the methodology developed for the optimization problems used in the wind-hydro-pump storage coordination. The optimization framework introduces the two strategies proposed in the dissertation: stochastic model for day-ahead optimization and operational management strategy. The strategies and its constrains concerning are addressed in detail in the succeeding sections.

Chapter 4 presents the results and the analysis of the results obtained. The stochastic results are compared with a deterministic approach (point forecasting) in order to evaluate the performance. The last section shows the results considering a large-scale optimization, which considers 3 months of wind and prices data.

The conclusions drawn from this work are presented in Chapter 5. A comparison table shows the differences and conclusions between the cases used as input in the algorithms. An overall critical analysis and some recommendations for future work are also presented.

Chapter 2

Background and State of the Art

This chapter provides a literature review of various works presented in the past decade regarding the independent or joint operation of wind farms and hydro power plants.

Initially a brief description of the Iberian electricity market is presented, followed by a a description of the two most common forms of delivering wind power forecasting: point and uncertainty forecasting. Emphasis is given to the later, since it is the method that reveals more interest regarding this dissertation.

The Wind-Hydro strategies are divided into three parts: Hydropower Plants bidding Strategies, Wind Farms Bidding Strategies and Wind-Hydro Coordination.

In the end, it is presented a comparison table between all the works studied and this dissertation, covering the uncertainty representation, the objective function and the representation or not of the decision maker attitude towards risk.

2.1 Iberian Electricity Market - MIBEL

The Iberian Electricity Market, MIBEL, is the electricity market of Portugal and Spain and is divided into two categories: the spot market where energy blocks and ancillary services are traded for immediate physical delivery and the futures market where the delivery is at a later date and may not involve physical delivery, as is explained in Bessa [5].

In this section emphasis is given to the electrical energy spot market, which is divided into two markets: Day-Ahead and Intraday.

In Figure 2.1 is represented the structure of the electricity market.

2.1.1 Day Ahead Market

The Day-Ahead Market(DA) is responsible for most of the energy transactions and it operates in Day D with the responsibility to negotiate energy for Day D+1.

The DA energy market is a double-side auction, where agents with generation units submit sell bids and agents with loads submit buy bids. If the agent is in the supply side, the bid reflects the minimum price that the agent is willing to receive for the amount of energy sold. However, if

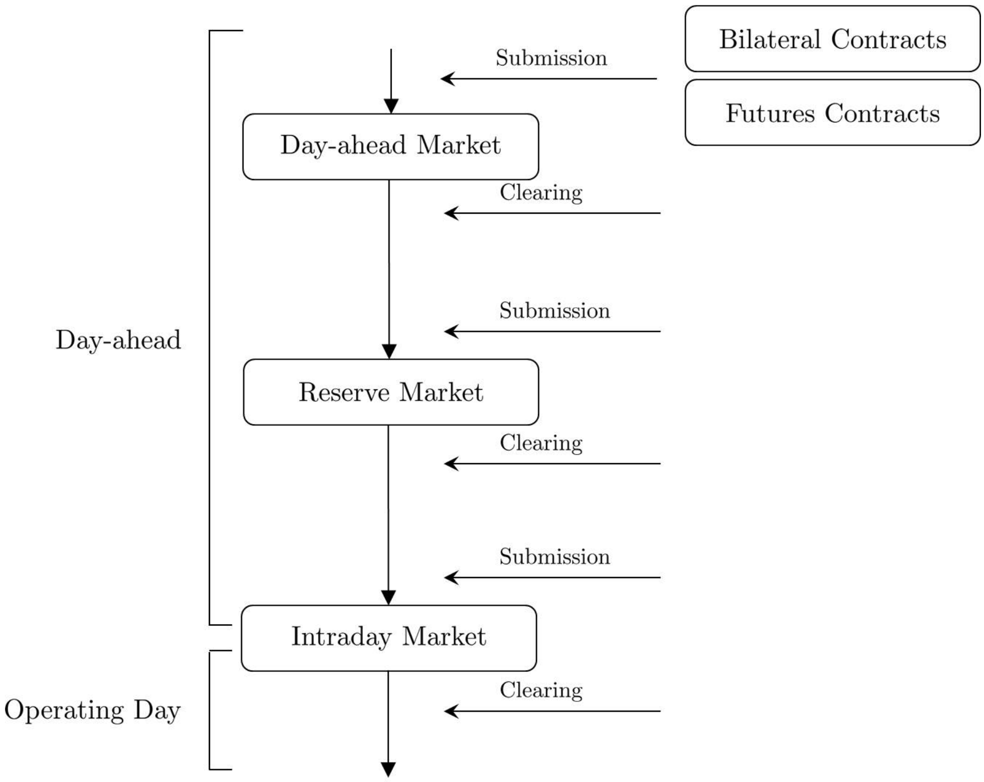

Figure 2.1: Structure of the Iberian Electricity Market - Figured from Corchero and Heredita [6]

the agent is in the demand side, the bid reflects the maximum price that the agent is willing to pay for the amount of energy bought.

The buy orders are ordered by ascending price (supply curve) and the sell bids are ordered by descending price (demand curve). The interception of the curves defines the market-clearing price and the amount of energy negotiated. Independently of the initial bids, all the agents pay/sell the electrical energy at this price value.

All the agents operating in the MIBEL have to present, until 12h00 (Spain time), buy and sell hourly bids that cover all 24 hours of the D+1 Day.

2.1.2 Intraday Market

The operation of Intraday (ID) and Day Ahead Markets are similar, the difference being the operation day, since the DA operates in day D and the ID in D+1.

The aim of the Intraday Market is to minimize imbalances between contracted energy in the DA market and the real energy produced, by using additional and/or more accurate information to correct the bids made in the previous day. This may occur due to forecasting errors, congestion in the transmission lines or unscheduled power outages from malfunctioning generators.

Since imbalances may be positive or negative, supply side agents can submit buy bids and an agent in the demand side may submit sell bids.

In the Iberian market the intraday market operates 6 times throughout day, with sessions every 4 hours.

2.2 Wind Power Forecasting

Forecasting models are used to suppress the variability and uncertainty in the wind power generation induced by the wind speed and direction fluctuations.

A Wind Power Forecasting (WPF) system uses as input data from different sources, such as: numerical weather prediction models (NWP), local meteorological measurements, wind power observation collected from supervisory control and data acquisition (SCADA) and includes data describing the real-time state and characteristics of the wind power plant, as it is explained in Botterud *et al.* [7].

Monteiro *et al.* [8] address two commons forms of delivering the wind power forecast: point forecast and uncertainty forecast, both addressed in this section.

2.2.1 Point Forecasting

From the wind power state of the art elaborated by Monteiro *et al.* [8] one concludes that nowadays most of the existing wind power prediction methods provide end-users with point forecasts.

A point forecast represents a single value for each look-ahead time horizon, which contains the conditional expectation at each time step [8]. The parameters of the models involved are commonly obtained with minimum least square estimation or other cost functions like it is presented by Bessa *et al.* [9].

An example of point forecast for a given time horizon is represented in Figure 2.2.

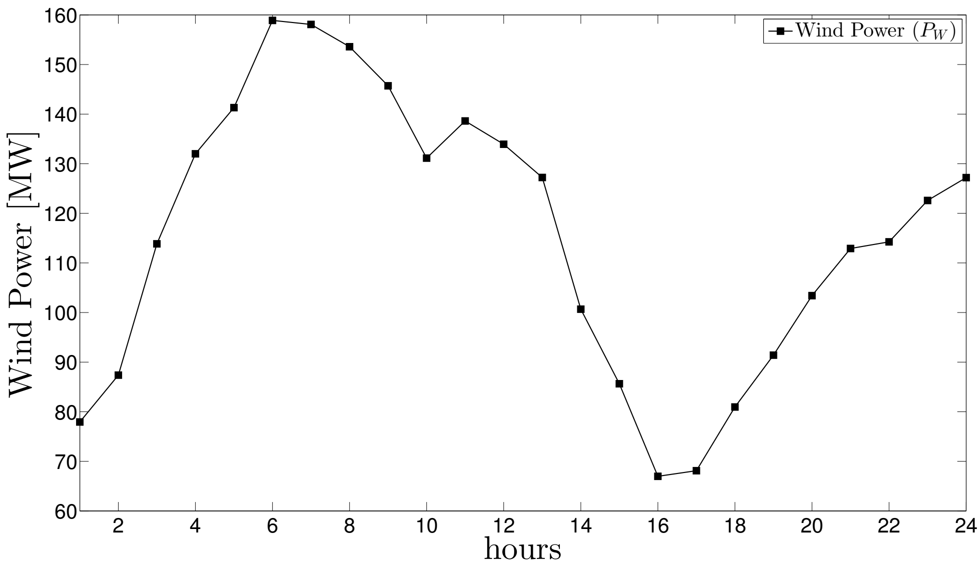

Figure 2.2: Example of point forecast.

2.2.2 Uncertainty Forecasting

The highly variability of point forecasting accuracy has made recent research works focus on associate uncertainty estimates with deterministic forecasting, for each time step uncertainty forecasts can take the form of probabilistic forecast, e.g. quantiles, risk indices or short-term scenarios with temporal and/or spatial dependency of errors.

2.2.2.1 Probabilistic Forecasting

Although the probabilistic predictions can be represented in the form of a quantile, interval or density forecast the basic unit to be considered is the quantile, since the other two are expressed in terms of two or more quantiles.

Considering a cumulative distribution function of wind power, a quantile marks the boundary of two subsequent equal-sized data subsets and the quote of two equally distant quantiles in terms of probability creates a forecast interval. As the wind power production distribution is not symmetrical, the intervals do not have the same distance towards the median.

Figure 2.3, extracted from the work of Pinson *et al.* [10], represents a interval forecast with intervals produced with an adaptive quantile regression. The quantiles showed vary from $Q_{10\%}$ to $Q_{90\%}$ with forecast intervals created from quantiles 10 percentage points apart.

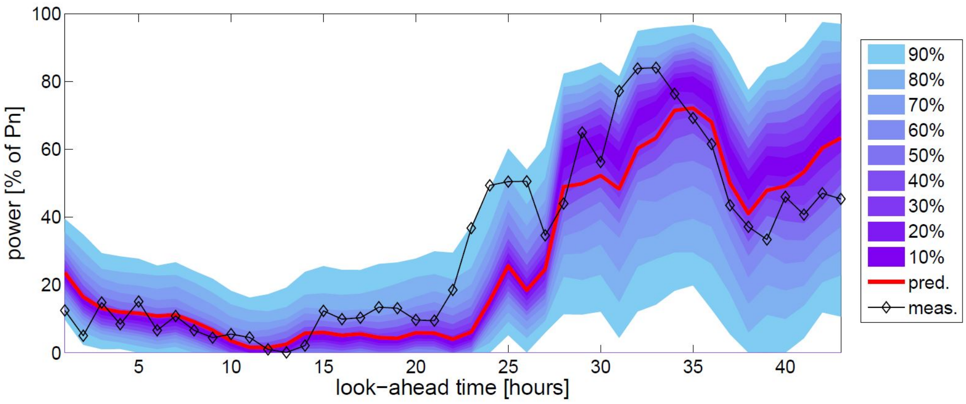

Figure 2.3: Example of a density forecast produced with quantile regression [10]

2.2.2.2 Prediction risk indices

Due to wind and weather dynamics the precision of wind forecast varies throughout the time horizon with periods in which, regardless of the forecast method employed, the accuracy of the prediction will be superior than in others. To account this uncertainty risk indices can be associated with point forecasting allowing decision makers to improve and adapt their operational strategies to every situation.

Pinson *et al.* [11] proposes a definition of prediction risk indices. The risk index assigns a weight to the prediction, where a lower risk index is associated with an higher weigh which corresponds to a more accurate forecast. The value of the weighs associated with WPF have a decreasing pattern throughout the time horizon, thus reducing the significance of predictions that are far from the time origin.

In Figure 2.4, it is represented the relative energy imbalance in order of the Normalized Prediction Risk Index (NPRI) of a Danish offshore wind farm. As the figure points out, there is an almost linear increase of the energy balances expected (resultant from WPU) in order of the risk indices values. Enhancing the relation between the risk indices and the accuracy of the forecast.

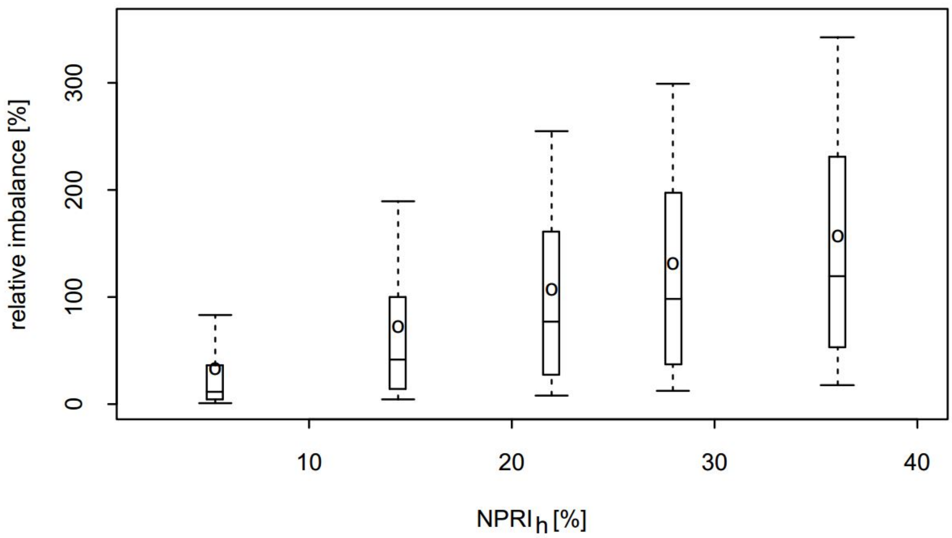

Figure 2.4: Conditional probability diagram giving the relation between Normalized Prediction Risk Index and level of energy imbalance [11]

2.2.2.3 Short-term Scenarios

Probabilistic forecasts are generated on a per lead-time basis i.e., marginal distributions, so they do not account the development of prediction errors throughout time, failing in providing information about the temporal and spatial dependency of errors [10]. This affects the efficiency in many time-dependent and multi-stage decision-making processes, such as the wind-hydro coordination problem, where decisions are made based in a 24-hour forecast window. In order to account for the interdependence structure of the prediction errors short-term scenarios are created.

The use of scenarios gives the decision maker the possibility to explore multiple wind power generation possibilities for a given time horizon, allowing the selection of a single operation point that minimizes the energy imbalances of every scenario.

For example, in this dissertation, for each wind power generation scenario the algorithm creates different solutions of pump power and reservoir energy levels. All of which have to satisfy the constraint of the optimization problem. In contrast, if point forecast predictions were used only one solution would be defined, therefore being more dependent of wind power prediction errors.

The method used to generate scenarios of wind power generation is proposed by Pinson *et al.* [12] and takes as inputs a time adaptive conditional kernel density estimation, presented by Bessa *et al.* [13], and also the observed wind power generation. Assuming that the probabilistic forecasts are reliable, the forecast errors are made Gaussian by applying a transformation with the inverse of the Gaussian cumulative distribution function. This results in a Gaussian random variable with zero mean and unit standard deviation. Considering the vector with all the forecasts for each look-ahead time-step, it is assumed that the random vector follows a multivariate Gaussian distribution, with mean values being a vector of zeros and a covariance matrix. The temporal interdependence structure is represented by the covariance matrix, which is recursively estimated because of the nonstationary characteristics. Through sampling from a inverse cumulative distribution function, a specified number of scenarios is generated.

In Figure 2.5 is represented a set of 50 scenarios created with method described.

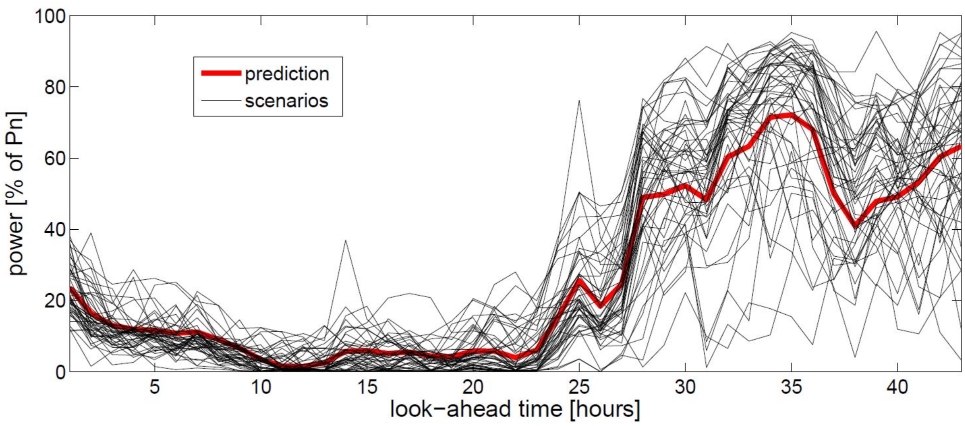

Figure 2.5: Example of wind power point predictions with 50 alternative scenarios [10].

2.3 Hydropower Plants Bidding Strategies

A hydropower plant system is mainly composed by a hydroelectric generator and a reservoir. The coordination between power generation and market prices is small and proportional to the storage capacity at the reservoir. For instance a hydroelectric dam with large reservoir capacity has the ability to store water and only generate electricity when the period is more profitable, however a run-of-river central does not have this possibility due to its lack of storage.

To increase the systems flexibility and profit a pump unit is installed, adding the possibility to use off-peak electricity to pump water from a lower reservoir to a higher elevation and generate electricity at peak hours.

In the work of Tsai *et al.* [14] an evolutionary algorithm uses actual Market Clearing Prices curve obtained from the ERCOT market in order to decide the bidding strategy in both day-ahead ancillary service market and real-time balancing energy service market aiming to maximize the profit. The numerical simulation results showed that that a pumped-storage unit has ability to make profits due to its outstanding fast response time, ramp rate and startup and shutdown time. Kazempour *et al.* [15] propose a self-scheduling bidding methodology to maximize the expected profit of a company comprised of several cascaded hydro plants along a river basin as well as pumped-storage plant, through participating in the day-ahead energy and ancillary service markets.

2.4 Wind Farm Bidding Strategies

Wind Farm systems do not have storage units and therefore no ability to compensate imbalances between contracted and produced energy. Due to the low efficiency of deterministic forecasts in this type of problems, it is important for wind farm operators to apply scheduling and trading strategies that reflect the uncertainty presented in wind generation.

Literature review reveals that the bidding strategies take focus on minimize the regulation costs induced by positive and negative imbalances, taking in account the uncertainty present in both wind and price forecast. In order to include the decision maker attitude towards risk different trade-offs strategies can be applied.

A risk-based decision approach is proposed by Bourry *et al.* in [16] aiming to minimize regulation costs. Two sources of uncertainty were accounted: the wind power uncertainty, expressed as a probability density function, generated with Kernel Density Estimators (KDE) and the uncertainty associated with the prediction of regulation costs for positive and negative imbalances. The market risk is measure with Conditional Value at Risk (CVaR), and a trade-off value was used. In a case study of a wind farm located in the North West of Denmark, the results showed an high sensibility to price forecasts with a 100% increase in revenue with perfect price prediction.

A similar approach is used by Botterud *et al.* [17], where a KDE generates wind forecasts but the decision maker risk preferences are reflected in the choice of one of 3 objective functions and corresponding parameters: risk neutral expressed in an expected value function, a linear trade-off function with EV and CVaR and an exponential utility function for modelling risk aversion.

Pinson *et al.* [18] compare the value of using point forecasting and probabilistic forecasting methods for minimizing the regulation costs. The bidding strategies are evaluated with a performance ratio which is calculated over a certain period of time by normalizing the actual revenue by the revenue that would be obtained if one had the possibility to use perfect forecasts.

This work also consider the use of two possible strategies: probabilistic choice and risk averse. The first aims to minimize the expected regulation costs, the other to minimize the risk of large loss, thus minimizing the worst possible scenario using a minmax approach.

2.5 Wind-Hydro Coordination

Wind farms have small controllability due to the variability of the wind speed and direction. One solution to overtake this problem consists in coordinate wind and hydro generation by adding a Pumping-Hydro Storage (PHS). Thus increasing the systems flexibility and profitability.

The optimization derived from the joint operation can be performed in two different moments:

- Day Ahead: This action is performed before the operating day by using price and wind forecasts to optimize the energy bids made to the day-ahead market. Water is pumped into the reservoir when prices are low, and used to generate electricity afterwards when prices are higher. Thus performing price arbitrage.

  In Figure 2.6, it is illustrated the typical operation of a pump storage unit. In the period b, the pump unit takes advantage of the lower spot market prices to pump water into the reservoir. Then, when a more profitable opportunity arises (period d) the hydro power plant generates energy from the stored water.

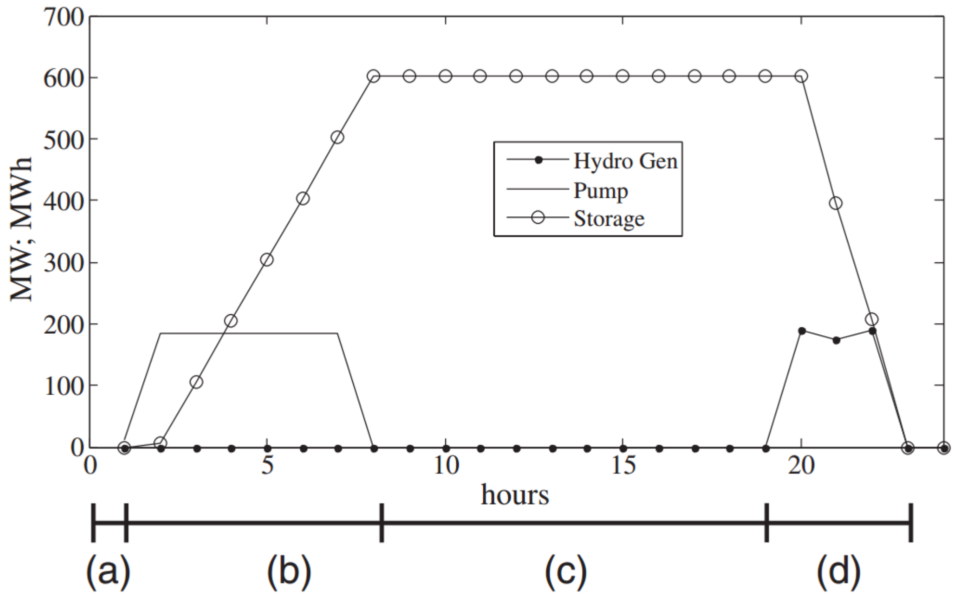

Figure 2.6: Typical operation of a water storage unit - Figure extracted from the work of Castronuovo *et al.* [19]

- Operational Strategy: This operation is conducted to minimize the difference between contracted and generated electrical energy. This is done by storing energy during periods when the real wind power is higher than the forecast and by using hydro generation for filling wind power gaps.

In this section the different strategies, from the literature, to coordinate wind an hydro generation will be reviewed.

2.5.1 Deterministic Wind-Hydro Coordination

To analyse the possibility to increase the economical benefits generated by a wind farm, Costa and Bourry [20] explore the operation of both wind farm and storage as a virtual power plant (VPP). The optimizing problem is divided in two phases and aims to find the maximum expected revenue of the system. The first schedules the day ahead market offers, considering the VPP to be a price taker with possibility to import energy. The second phase focus on compensating any imbalance in power production induced by prediction errors.

Although a statistical method based in Kernel Density Estimators is used to create wind power forecasts, only a single value (the mean of the distribution) for each lead-time was considered. The spot price forecasts were computed using a simple method, which consists in taking the last available measure price for a given hour. A dynamic programming optimization method was used to solve the virtual power plant scheduling problem.

For each simulation, that can accommodate several days, the initial and final energy level of the reservoir are defined as 50% of the maximum capacity. From the second day till the end of the simulation, the final level of the energy storage device is define by the operational strategy of the previous day.

In sections 3.1 and 3.2 of Castronuovo *et al.* [19] work a different approach is used, where the day ahead scheduling process does not have the possibility to buy energy from the market, thus using only power from the wind farm to operate the pump unit. Therefore wind prediction errors will affect not only the wind production but also the storage unit energy level.

The day ahead scheduling is performed by a linear programming algorithm using a statistical forecasting approach from the ANEMOS.plus platform to provide point forecasts. For the operational strategy an empiric solution is proposed. Ratio coefficients are calculated from the day-ahead schedule in proportion to the wind forecast and then re-calculated with the realized wind values. Hence creating new set points for the operation of these units. An evaluation is carried out to ensure that technical constraints are not violated, and if they are, corrective actions, defined by standard procedures, are applied to solve them.

The optimal sizing for the adequate coordination between the wind farm and the storage devices is also considered in the literature. In the work developed by Castronuovo and Peças Lopes [21], the optimal size of the water-storage unit is calculated in order to maximize the economic profit of the joint operation. The formulation uses a curve of minimum active power and, when there is not a feasible solution, it estimates the additional capacity of the water reservoir required to comply with the constraint.

The installed capacity of the pump station and the hydro generator was fixed in a value less than 20% of the installed capacity of the wind park and the storage capacity was defined to be equivalent to 2 hours of operation of the wind farm at nominal power.

A continuous variable is used to simulate dump loads, assuring that the output power is kept below the level accepted by the network. This is an optimistic assumption, because, unless the wind generator has Pitch control, the wind farm operator will restraint the power output by disconnecting wind generators, thus a discrete variable should be used. This strategy will result in larger gains, since the disconnection of wind generators will provoke, in general, a loss of production larger than the load dumping effect.

Given the flexibility of an water-storage unit it may be possible to perform energy arbitrage (buy energy at lower prices to sell at a more profitable period) at the same time as reducing the wind power imbalances. Since this may restrain the arbitrage's profit, the benefits of a wind-hydro operation in the perspective of the storage unit are discussed by Bathurst and Strbac [22]. Using a persistence forecasting model to predict wind power this work calculates the added value of the joint operation, in other words, the difference between the combined and solo operation. If the result is greater than zero then all participants will gain from this operation, however a negative result infers that one party may be free riding at the expenses of the other.

2.5.2 Stochastic Wind-Hydro Coordination

Probabilistic forecasts provide uncertainty information for each single time step in the future. A commonly used representation of uncertainty information is through non-parametric probabilistic predictions, such as quantiles, intervals, probability density functions and scenarios incorporating a temporal interdependence structure of prediction errors.

Castronuovo and Peças Lopes [23] suggests the use of a water storage unit to improve wind park operational economic gains and to attenuate active power output variations, by assuring a minimum power delivery to the grid, no matter the wind speed conditions. The model proposed uses Monte Carlo simulations to generate wind power time-series scenarios resulting in a stochastic representation characterized by two series of hourly values: wind power average value and its standard deviation magnitude.

Contrary to the wind uncertainty representation used in this dissertation the scenarios created by Castronuovo and Peças Lopes [23] lack the interdependence structure of the prediction errors, since the algorithm randomly generates scenarios for every day and hour regardless of the previous instances.

The algorithm consists in an optimized daily operation strategy determined by solving a linear hourly-discretized optimization problem using actual Portuguese wind energy remuneration, which are defined as specific tariffs, independently of the market price. For each scenario an optimization is performed, aiming to find the maximum expected value. The joint operation results are then compared with an only wind strategy.

In the work of Bourry *et al.* [24] the storage unit is only used to reduce the imbalances in the intra-day market, not participating in the day ahead bidding optimization. The day ahead algorithm uses a power curve modelling to consider wind power forecasts and uses real market prices in the simulations.

Gonzalez *et al.* [25] use short-term scenarios to represent the uncertainty about market prices and wind power generation. This work aims to minimize the expected regulation costs which are the difference between the contracted energy and the energy produced, affected by the imbalance prices.

In this paper, the authors penalize the absolute value of the imbalance at a given market price percentage, in other words, the positive and negative imbalances are equal and proportional to the market price. In the dissertation in question the positive and negative imbalances are not equal and constitute real data from the Portuguese energy market. To keep the optimization close to reality, integer variables were used to allow the consideration of multiple pump units and guarantee that hydro and pump units do not work simultaneously. This forced the use of a Mixed Integer Linear Programming algorithm.

A different approach of Wind-Hydro coordination is followed by Matevosyan *et al.* [26], where a multi reservoir system is coordinated with wind power. Both elements are owed by different utilities sharing the same transmission line, so coordination is necessary to avoid energy curtailments during congestion situations. The algorithm has two phases, first plans the hydro power without considering wind power (spot market) and then re-plans taking in consideration wind power uncertainty (spot and regulating markets). If congestion in the transmission is expected, then hydro power is retained in the reservoirs to allow the wind farm to produce all wind energy, being this operation paid by the wind utility.

The optimizing problem is formulated as a two-stage stochastic program, with spot prices and wind power uncertainty represented by short-term scenarios. The reservoir energy level is reset at the end of every week.

Most of the previous works analyse the storage action as internal (or strongly related) to wind power production, exclusively using the storage ability to compensate the wind power imbalances. However, this approach is not representative for large pumped stations in power systems. Duque *et al.* [27] aim to simultaneously optimize the revenue in the conventional operation of the storage plant and to offer a reserve for managing wind power imbalances.

The method described in Section 2.2.2 is used by Duque *et al.* [27] to generate wind power scenarios, thus taking into account the relationship between the errors at different time horizons and the conditional behaviour of the wind power prediction. From that scenarios prediction intervals are obtained and all wind scenarios with less than 10% probability are discarded, thus only compensating 90% of the imbalances. By reducing even more the band (compensating only 80% or 70% of the imbalances) the wind power producer decreases the reserve contracted in the hydro-pump plant, but with the economic risk of compensating imbalance costs in the reserve market.

The deterministic approach of Castronuovo *et al.* [19], presented in the previous section, was enhanced to accept probabilistic wind power forecast. The function, proposed in section 3.3 of the paper, places emphasis on risk-related aspects, allowing the decision maker to choose the level of risk he or she is prepared to accept and obtain the corresponding solution. To achieve this goal, a chance-constrained strategy was implemented.

Keko *et al.* [28] deliver a comparison of two uncertainty modelling approaches in the context of the optimization of a daily operation for a wind power plant combined with a small-scale pumped hydro storage. The first model is the same used by Castronuovo and Peças Lopes [23], and the second uses temporal scenarios generated according to the method expressed in Pinson *et al.* [12]. Despite the use of the same method to generate time-depend scenarios as this dissertation the methodology is different, since, in Keko *et al.* [28], for every scenario an optimal operation strategy is determined, instead of a single solution regarding all scenarios.

A methodology for dynamic sizing of energy storage based in the degree of risk that the wind power producer accepts to be exposed is presented by Pinson *et al.* [29]. With this approach the energy storage is used as a mean of risk hedging against penalties from the regulation market and opens the possibility to rent, to each producer, only the necessary daily storage capacity. Short-term temporal scenarios are created using the method described by Pinson *et al.* [12], and for each scenario a operation point is calculated leading to different potentially required storage capacities. Gathering the information in a histogram allows the authors to estimate the probability distribution of the necessary reservoir capacity. By quantifying the risk as a quantile of the distribution, the power producer may decide upon the necessary reservoir capacity based on the level of risk exposure.

2.6 Final Remarks

The strategies used in the independent or joint operation of wind and hydro systems are very sensible and dependent of wind and price forecasts. Therefore the choice of the forecast tool and method is of utmost importance.

Literature shows that, generally, forecasts with uncertainty representation show better results than those that use a deterministic approach.

Analysing the information from Table 2.1, where is shown a comparison between all the reviewed works in this chapter and this dissertation, one can derive the following conclusions:

- The use of point forecasting has been deprecated in favour of stochastic methods to represent wind power uncertainty;
- Even though some works use temporal scenarios to represent wind power uncertainty, their approach is different of the one taken by this dissertation, since calculate an optimal solution for every scenario instead of one solution considering all scenarios;
- The expected value of the systems revenue was the most commonly objective function for day-ahead bidding strategies;
- Utility functions and risk metrics have been used in wind farms bidding strategies. The consequences of its use in Wind-Hydro joint operations are yet to be studied;
- The use of operational strategies to coordinate Wind-Hydro bidding strategies and minimize power imbalances during operation day is still an unexplored area.

Table 2.1: Comparison between the literature reviewed

Work	Wind Uncertainty Representation			Objective Function			Operational Strategy
	Point Forecast	Quantiles	Temporal Scenarios	Expected Value	Utility Function	Risk Metrics	
Wind Farms Bidding Strategies							
Bourry and Juban, 2008 [16]		✓			✓	✓	n.a.
Botterud *et al.*, 2012 [17]		✓			✓		n.a.
Pinson *et al.*, 2007 [18]		✓			✓		n.a.
Wind-Hydro Strategies							
Costronuovo *et al.*, 2013 [19]	✓	✓		✓		✓	✓
Costa and Bourry, 2008 [20]	✓			✓			
Castronuovo and Peças Lopes, 2004 [21]	✓			✓			
Bathurst and Strbac, 2003 [22]	✓			✓			
Castronuovo and Peças Lopes, 2004 [23]		✓		✓			
Bourry, 2009 [24]		✓		✓		✓	✓
Garcia-Gonzalez, 2008 [25]			✓	✓			
Matevosyan and Söder, 2007 [26]			✓	✓			
Duque *et al.*, 2011 [27]			✓	✓			
Keko *et al.*, 2011 [28]			✓	✓			
Pinson *et al.*, 2009 [29]			✓	✓		✓	
This Dissertation	✓		✓	✓	✓		✓

Chapter 3

Optimization Problems for Wind-Hydro-Pump Storage Coordination

This chapter describes the methodology proposed by this dissertation. Two different algorithms are introduced, the stochastic day-ahead algorithm, which takes advantage of the wind power scenarios characteristics to proposed sell bids to the energy market and the operational management strategy that aims to suppress the imbalances between the contracted and real energy generated.

In the first section the optimization framework is described, where a brief definition of both algorithms is presented as well as the overall diagram of the operation. Sections 3.2 and 3.3 address in detail the objective functions and system constraints of the DA and OS optimization problems.

The last section points out the techniques implemented to improve the efficiency of the optimization algorithm used and reduce its computational time.

3.1 Optimization Framework

The optimization framework presented in this dissertation proposes two distinct algorithms with the aim of minimizing the imbalances incurring from the difference between contracted and real electric energy produced. The first algorithm is stochastic and defines the sell bids that will be presented to the electricity market and the second optimization strategy uses updated wind power forecasts minimize deviations between bids and actual values.

Figure 3.1 depicts a diagram illustrating the overall operation of both strategies. As it is shown, the Day-ahead Strategy (DA) uses as input short-term wind power scenarios and real market and imbalances prices. The algorithm performs an optimization that obtains the predicted values of hydroelectric ($\hat{P_H}$), and wind power ($\hat{P_G}$), generation for the next day, and the sum of these two variables is the amount of energy to be offered in the day-ahead market.

The accepted bids are then used as inputs in the Operational Management Strategy (OS), which, using updated wind power point forecasts and the last state of the system, performs a new optimization problem, updated every hour, to define new valid operation points (complying with the constraints of the system) for the Hydro-Pump unit in order to use the energy stored in the water reservoir to minimize imbalances between the bids offered in the day-ahead market and the real electric energy produced. The evaluation module combines the real energy generated by the system with the market and imbalance prices to find the real system's revenue.

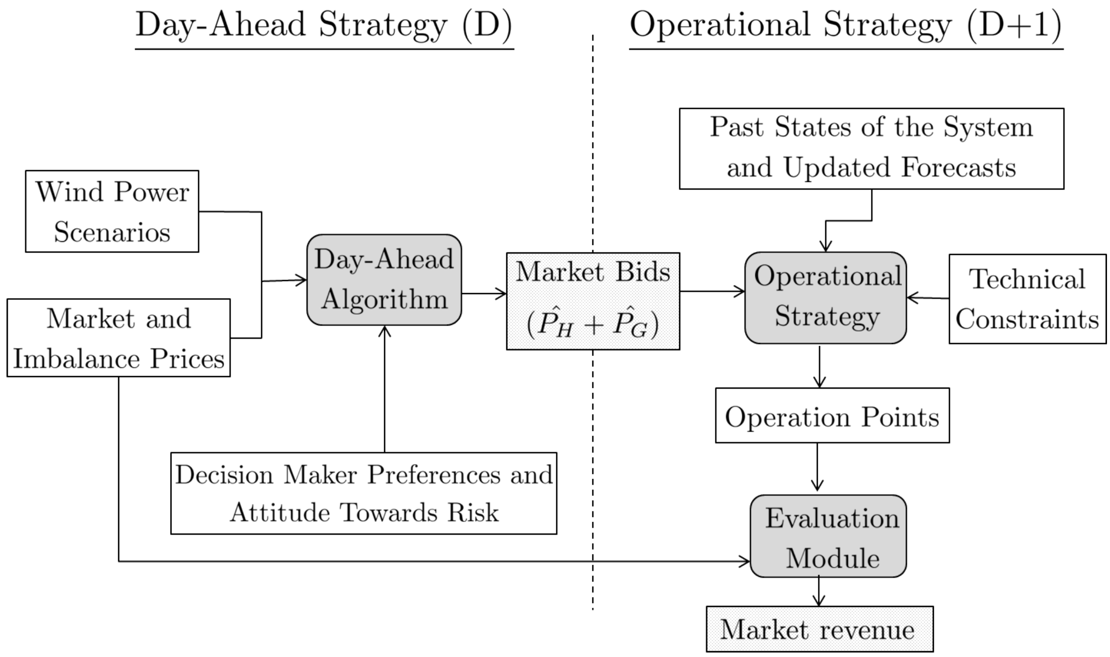

Figure 3.1: Diagram of the overall operation of the DA and OS algorithms

The stochastic DA algorithm contemplates the use of different objective functions that model two decision-making paradigms:

Expected Value (EV) - aims to maximize expected revenue of the system;

Expected Utility (EU) - which has the possibility to use a unidimensional utility function to account for the decision maker's attitude towards risk and a multi-attribute additive utility function to take in consideration the decision maker's attitude towards the waste of renewable energy. Both possibilities aim to maximize the objective function expected utility;

Despite the diversity of objective functions, the stochastic DA system constraints are common to all.

This dissertation uses the formulation presented by Castronuovo and Peças Lopes [23] as a foundation for the expected value objective function and for the establishment of the system constraints.

3.2 Stochastic Model for Day-ahead Optimization

The Day-ahead optimization consists in taking advantage of the system's storage capacity to perform price arbitrage, by using the pumping unit to store wind energy produced during low-price periods to be generated at a more profitable time (high price hours) by the hydro unit, and to reduce regulation cost resulting from the imbalances between contract and real energy generated. In this formulation it is assumed that all the energy delivered to the grid is from wind energy (hydro and wind farm) which generalizes the problem to other storage technologies, such as small-scale storage.

As mentioned in section 2.1.1 all the agents operating in the electricity market have to present sell bids that cover all 24 hours of the next day, thus forcing the wind energy producers to rely on wind power forecasting tools to schedule the offers. In this dissertation the rules of the Iberian electricity market (MIBEL) are followed.

In this dissertation a Gaussian copula function is used to generate wind power scenarios, based in the work of Pinson *et al.* [12], that provide information about the temporal dependency of errors through the prediction horizon, as explained in section 2.2.2.

In a Wind-Hydro coordination, the electrical energy sell bids made to the energy market are the sum of the energy directly delivered to the grid from the wind farm (P_G) and the electric energy from the hydroelectric power unit (P_H). Therefore the day-ahead optimizing algorithm defines this values as global variables and independent to every wind power scenario (only a value for each i hour is obtained from the optimization). Figure 3.2 shows the solution found by the stochastic day-ahead optimization for the P_G and P_H regarding a case study with 30 wind power scenarios. As is shown, and despite the number of scenarios considered by the algorithm, there is only a single hourly value for each variable in question.

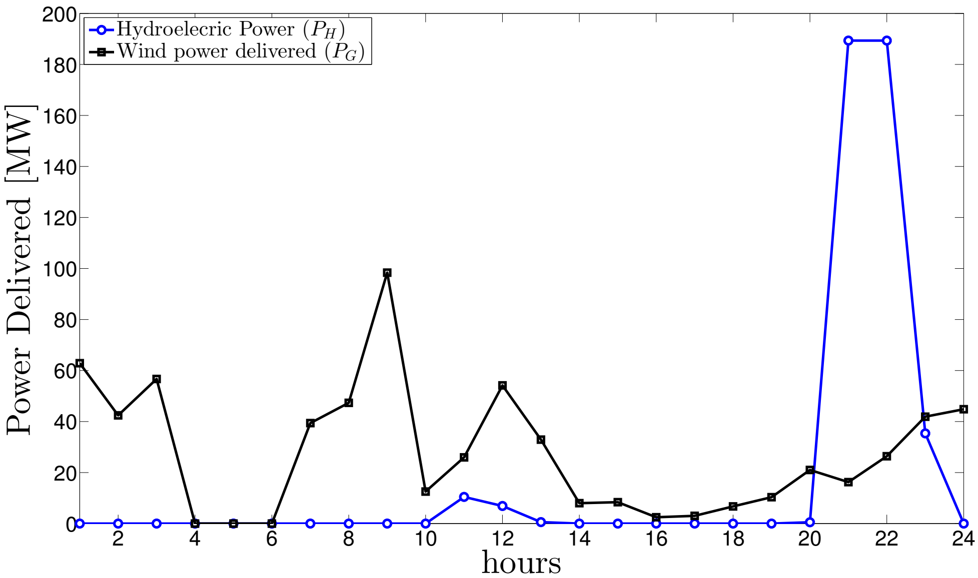

Figure 3.2: Wind and Hydroelectric Power delivered in every hour

Aside from the P_H and P_G, all the other variables are divided in sub-variables, each one related to a single wind power scenario, thus a set of multiple valid solutions (complying with all system's constraints) is created and the optimization algorithm evaluates them as a whole. Figure 3.3 exemplifies the previous statement by showing the Pumping Power (P_P) for every hour in a case study with 30 wind power scenarios. As shown, for every hour the variable P_P has 30 scenarios of operation.

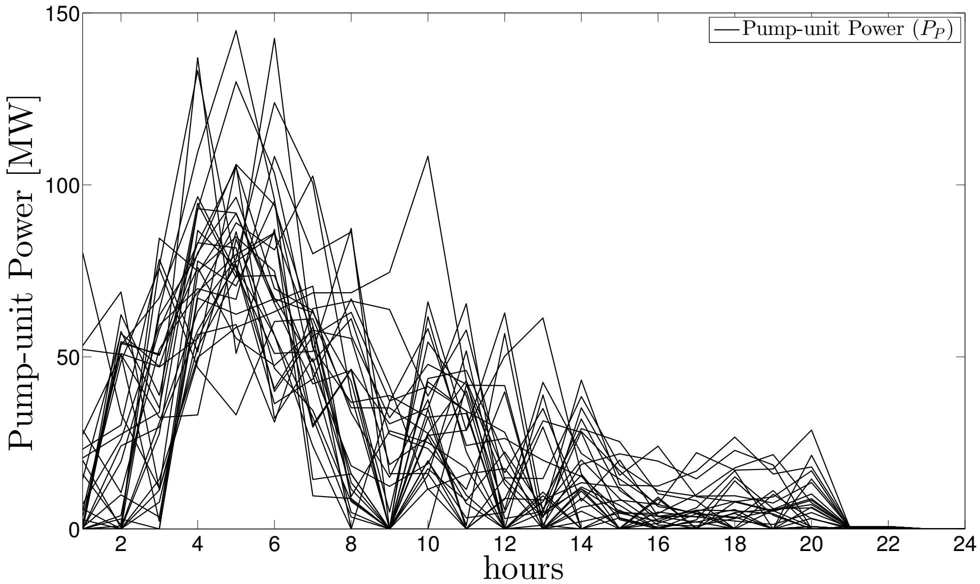

Figure 3.3: Pumping Power delivered in every hour

Global and scenario-dependent variables are distinguish through a set of indices. To global variables an hourly index i is assigned, i.e. P_{Hi}, for the others a scenario index s is used, i.e. $P_{Ps,i}$. Table 3.1 defines the variables used by the day-ahead optimization algorithm.

Table 3.1: Variables used in the Day-ahead Algorithm (Bold:decision variables)

Global Variables	$\boldsymbol{P_{Hi}}$	Hydroelectric power at hour i
	$\boldsymbol{P_{Gi}}$	Wind Power directly delivered to the grid at hour i
Scenarios Variable	$\boldsymbol{P_{Ps,i}}$	Pumping Power in scenario s at hour i
	$E_{s,i}$	Energy stored in the reservoir in scenario s at hour i
	$T_{s,i}$	Regulation costs in scenario s at hour i
	$d_{s,i}$	Power Imbalances in scenario s at hour i
	$\boldsymbol{P_{DLs,i}}$	Dumping power loads in scenario s at hour i

Both global variables, P_H and P_G, represent the electric energy delivered to the grid at an hour i by an hydroelectric unit and a wind farm, respectively.

The pumping power, P_P, indicates the amount of wind power consumed by the pumping unit to store water in the reservoir. The current energy present in the reservoir is expressed by E and the amount of renewable energy wasted is represented by P_{DL}.

Power imbalance, d, is defined as the difference between the electric energy globally predicted to be delivered to the grid and the amount of electric energy available in that specific scenario. In other words, the algorithm, after evaluating all the wind power scenarios provided, finds an optimal value of P_G and d_s represents the difference between that value and the available power at the scenario s, which can be positive, negative or null.

The regulation costs, $T_{s,i}$, are the value paid by the systems operator in order to compensate the energy market for the power imbalances (d). Positive and negative imbalances are taxed differently, thus the regulation costs are calculated according to Equation 3.1. Positive imbalances force the market to pay a down-regulation price (p_i^+) to put in operation reserves to decrease generation, in contrast negative imbalances force the market entity to put in operation reserves in order to increase electric energy generation, therefore the system's operator must pay a up-regulation price (p_i^-).

$$T_{s,i} = \begin{cases} d_{s,i} \cdot (p_i - p_i^+), & \text{if } d_{s,i} \geqslant 0 \\ -d_{s,i} \cdot (p_i^- - p_i), & \text{if } d_{s,i} < 0 \end{cases} \tag{3.1}$$

From the variables presented in Table 3.1, only P_H, P_G, P_P and P_{DL} are decision variables, since the others are dependent on the values that these variables take.

With 2 global variables and 5 scenario-dependent variables, the stochastic DA optimization algorithm requires $(2 + 5 \cdot s)$ variables per hour. Since the electricity market bids are made in a daily basis ($n = 24$), the total number of variables is: $n \cdot (2 + 5 \cdot s)$, therefore a case study with 100 wind-power scenarios requires a total of 12 048 variables.

3.2.1 Objective Functions

As previously mentioned, the day-ahead algorithm can have different objective functions, those being:

- Expected Value (EV)
- Expected Utility Function (UF)
  - Unidimensional
  - Multi-attribute

In this dissertation point forecasting is used as a comparison model to evaluate the benefits of wind power short-term scenarios. The objective functions and system constraints are the same for PF and wind power scenarios, the only difference is the definition of $S = 1$, with S being the number of scenarios considered, since using point forecasting is the same as considering a stochastic case with only 1 scenario.

In the following section the objective functions will be described in detail.

3.2.1.1 Expected Value

The Expected Value (EV) objective function, Equation 3.2, aims to maximize the Wind-Pump-Hydro system revenue by minimizing the associated costs, with an optimization period of 24 hours ($n = 24$).

$$\max \text{EV} = \max \sum_{s=1}^{S} \rho_s \cdot \sum_{i=1}^{n} \left[p_i \cdot (P_{Gi} + P_{Hi} + d_{s,i}) - T_s - c_{pump} \cdot P_{Ps} - c_{hydro} \cdot P_{Hi} \right] \tag{3.2}$$

The sum of $P_{G\,i}$, $P_{H\,i}$ and $d_{s,i}$ represents the electric energy offered to the energy market, therefore is multiplied by the spot market price p_i for the hour in question. The power imbalance is considered in the equation, because if a scenario has surplus ($d_{s,i} > 0$) or deficit of wind power ($d_{s,i} < 0$) its remuneration will be different than the global profit of the bid. Costs associated with the use of hydro and pumping units are considered, respectively, in the c_{hydro} and c_{pump} constants, although, in this dissertation both operation costs were considered negligible. The variable T_s is already affected by the correspondent regulation price, hence the lack of any price factor (Equation 3.1).

As the formulation suggests, for each scenario the correspondent revenue is calculated. The sum of each scenario's revenue affected by its probability of occurrence results in the expected daily global revenue of the system.

3.2.1.2 Unidimensional Utility Function

Utility functions (UF) can capture the decision maker attitude towards risk [30].

The risk taking attitude is addresses with the concept of *certain equivalent* (CE), which is the certain amount that is equally preferred to an uncertainty alternative (UA) [31]. If a decision maker prefers to receive the *certain equivalent* rather than the uncertainty alternative it is considered as risk averse, while someone of prefers to receive the uncertainty alternative rather than the *certain equivalent* is considered risk prone.

It is the interaction with the decision maker that shapes the utility function, following the process described in [32]. If the DM always prefers the certain equivalent, the utility of the CE is greater than the utility of the uncertainty alternative, therefore the utility function will be concave. On the other hand, a prone to risk decision maker will have a convex utility function, which is the result of having a higher utility of the UA than the certain equivalent.

In Equation 3.3 it is expressed the objective function used in this dissertation that aims to maximize the expected utility.

$$u(z) = \frac{1}{1-e^{\beta}} \cdot \left[1 - e^{\frac{\beta \cdot (z-min)}{max-min}} \right], \quad U(z) \in [0,1] \tag{3.3}$$

The *min* and *max* constants are the bounds of the function and β allows modelling different attitudes and degrees towards risk from the decision maker.

Figure 3.4 shows a graphic representation of the utility function introduced in Equation 3.3. Two tendencies are shown, one averse and the other prone to risk, which result from the value of the β parameter. $\beta < 0$ means constant aversion to risk, while $\beta > 0$ results in a constant proneness towards risk.

The absolute value of β defines the shape of the utility function, where the greater it is the stronger is the attitude of the decision maker. In Figure 3.5 are represented the attitude towards risk of four different decision makers. As its shown the degree of risk of the DM strongly influences the shape of the utility function, with bigger absolute values of β representing a more strong attitude towards risk.

By adjusting this function to the characteristic of the optimization problem addressed in this dissertation one obtains the following objective function.

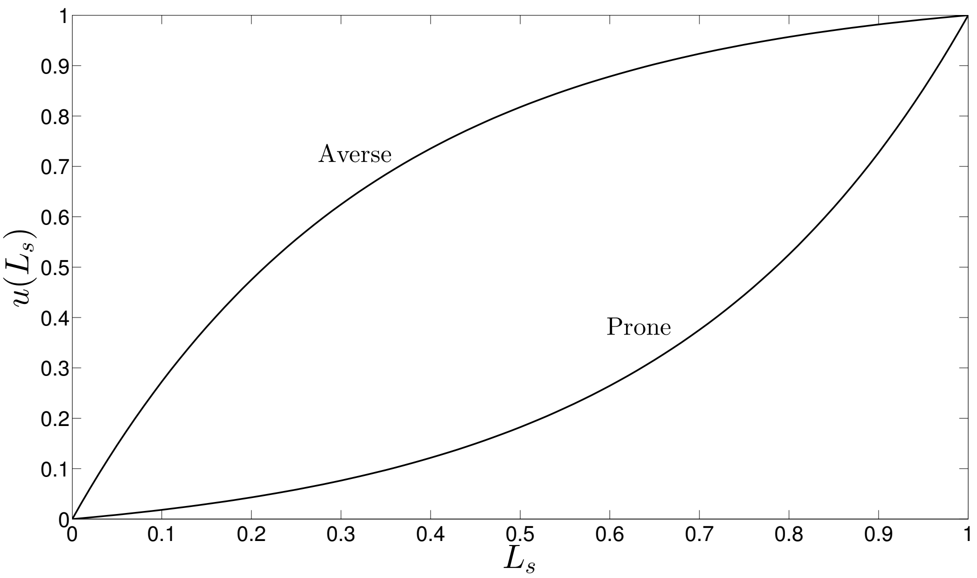

Figure 3.4: Attitudes towards risk in utility function - Risk Averse and Risk Prone

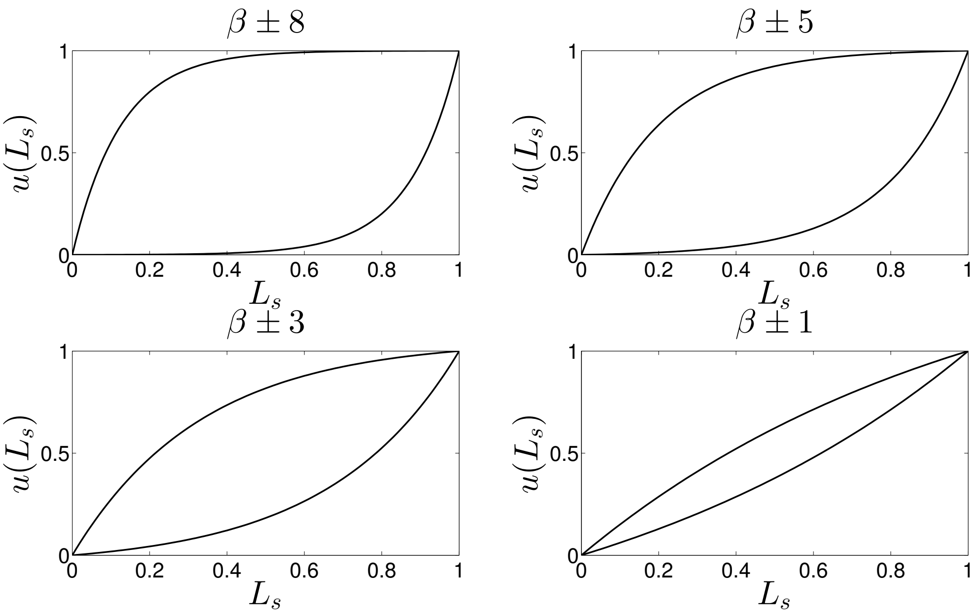

Figure 3.5: Influence of the β parameter in the slope of the utility function

$$\max \text{EU} = \max \sum_{s=1}^{S} \rho_s \cdot U_s(L_s) \tag{3.4}$$

$$\text{s.t.} \qquad U_s(L_s) = \frac{1}{1-e^{\beta}} \cdot \left[1 - e^{\dfrac{\beta \cdot (L_s - L_{min})}{L_{max} - L_{min}}} \right], \quad U_s(L_s) \in [0,1] \tag{3.5}$$

$$L_s = \sum_{i=1}^{n} \left[p_i \cdot (P_{Gi} + P_{Hi} + d_{s,i}) - T_{s,i} - c_{pump} \cdot P_{Ps,i} - c_{hydro} \cdot P_{Hi} \right] \tag{3.6}$$

Equation 3.6 calculates the total daily revenue of the scenario, as explained in the previous section, this value is then used to find the utility of the scenario with Equation 3.5. This process is repeated for all wind power scenarios.

The objective function in 3.4 sums the individual utility of each scenario multiplied by its probability of occurrence, which results in the daily expected utility of the system. The algorithm performs the optimization aiming to find optimal solution which ensures the maximum expected utility of the system.

The boundaries of the utility functions are assured by the constants L_{max} and L_{min} and are based in the best and worst revenue possible. The maximum is establish considering a day in which both hydro and wind units operate at nominal power with maximum market remuneration. The minimum is the expected revenue in a day with zero electric generation and maximum regulation costs, in other words, is the equivalent of offering to the energy market $(P_H^M + P_G^M)$ without being able to provide any of it, hence paying a regulation tax equivalent to the that amount of energy multiplied by the maximum negative imbalance price, p_{max}^-.

$$L_{max} = p_{max}^+ \cdot n \cdot (P_H^M + P_G^M) \tag{3.7}$$

$$L_{min} = -p_{max}^- \cdot n \cdot (P_H^M + P_G^M) \tag{3.8}$$

With the use of the utility function an agent with an averse attitude towards risk is expected to neglect the possibility of having a very profitable scenario with low probability of occurrence in favour of a solution that gives more guarantees of a certain profit. A decision maker with a more risk prone attitude will favour the chance of having a very good scenario and depreciate the rest.

3.2.1.3 Multi-attribute Utility Function

In the previous objective functions the possibility to waste renewable energy, $P_{DLs,i}$, is considered cost free, both in economic and social terms. The Multi-attribute Utility Function (MUF) introduces the quantification of such waste by using an multi-criteria utility function which adds the decision maker attitude towards this attribute.

The MUF combines a linear utility function, which regards the revenue of the system, $U(L_s)$, and an exponential utility function that accounts the wasted renewable energy, $U(W_s)$. Therefore the objective function is the sum of both utility functions affected by the probability of the scenario and the decision maker parameters (k_1 and k_2), that must be found in interaction with the decision maker (e.g., finding two indifferent solution). Equations 3.9 - 3.13 show the proposed methodology.

$$\max \text{EU} = \max \sum_{s=1}^{S} \rho_s \cdot [\, k_1 \cdot U_{L_s}(L_s) + k_2 \cdot U_{W_s}(W_s) \,] \tag{3.9}$$

$$\text{s.t.} \qquad U_s(W_s) = \frac{1}{1-e^{\beta}} \cdot \left[1 - e^{\dfrac{\beta \cdot (W_s - W_{max})}{W_{min} - W_{max}}}\right], \quad U_s(W_s) \in [0,1] \tag{3.10}$$

$$W_s = \sum_{i=1}^{n} P_{DL_{s,i}} \tag{3.11}$$

$$U_{Ls}(L_s) = \frac{L_{max} - L_s}{L_{max} - L_{min}}, \quad U_{Ls}(L_s) \in [0,1] \tag{3.12}$$

$$L_s = [p_i \cdot (P_{Gi} + P_{Hi} + d_{s,i}) - T_{s,i} - c_{pump} \cdot P_{Ps,i} - c_{hydro} \cdot P_{Hi}\ ] \tag{3.13}$$

The exponential utility function $U(W_s)$ is similar to the one presented in the previous section, but this one is affected by the curtailed wind energy in the scenario (W_s), rather than the system's revenue, and is calculated according to Equation 3.11.

$U(L_s)$, uses a linear utility function to represent the revenue of the pump-hydro storage system, and L_s is expressed as the expected value of the revenue, as presented in the previous sections.

Constants L_{max} and L_{min}, which define boundaries in the linear utility function, are the same as in the UF.

The W_{max} and W_{min} limits represent the daily maximum and minimum wasted renewable energy, thus the lower limit is equal to zero and the upper is defined as the wind farm's nominal power multiplied by the number of hours in a day, n.

$$W_{max} = n \cdot P_G^M \tag{3.14}$$

$$W_{min} = 0 \tag{3.15}$$

$$L_{max} = p_{max}^{+} \cdot n \cdot (P_H^M + P_G^M) \tag{3.16}$$

$$L_{min} = -p_{max}^{-} \cdot n \cdot (P_H^M + P_G^M) \tag{3.17}$$

The parameters of the multi-criteria utility functions (k_1 and k_2) are defined in interaction with the decision maker. From this interaction an indifferent solution is found, and, consequentially, a trade-off between profit and renewable energy wasted is established. This dissertation considers three different decision makers and Table 3.2 points out the trade-off and indifferent solution correspond to each decision maker considered.

Solution A and Solution B are both valid solutions obtained from the optimization problem and represent solutions for which the decision maker is indifferent. For example, the Decision Maker A is indifferent between a solution that provides 110 500 € with the waste of 150 MWh of renewable energy and another solution with a profit of 80 500 € without wasting wind energy. This results in a trade-off between profit and curtailed renewable energy of 200 € MWh, in other words, Decision Maker A will pay 200 € to decrease 1 MWh of wasted renewable energy.

Table 3.2: Attitude of different Decision Makers

	Solution A		Solution B		Trade-off
	$L(A)$	$W(A)$	$L(B)$	$W(B)$	
Decision Maker A	110 500 €	150 MWh	80 500 €	0 MWh	200 €/MWh
Decision Maker B	110 500 €	150 MWh	87 200 €	0 MWh	155 €/MWh
Decision Maker C	110 500 €	150 MWh	100 500 €	0 MWh	67 €/MWh

Knowing two solutions with equal utility and that the sum of the multi-attribute parameters must remain equal to the unit, it is possible to calculate the value of k_1 and k_2 by solving the equation system presented in 3.18.

$$U(A) = U(B) \iff \begin{cases} k_1 \cdot U_L(A) + k_2 \cdot U_W(A) = k_1 \cdot U_L(B) + k_2 \cdot U_W(B) \\ \\ k_1 + k_2 = 1 \end{cases} \tag{3.18}$$

The results in Table 3.3 show the different parameters of the multi-attribute utility function obtained from the solving of the equation system 3.18 with the information from Table 3.3.

Table 3.3: Multi-attribute Utility Function Attributes for each Decision Maker

	k_1	k_2
Decision Maker A	0.6603	0.3397
Decision Maker B	0.7141	0.2859
Decision Maker C	0.8536	0.1464

Note that an interpretation in terms of weights associated to the two attributes should not be derived, since the values of k_1 and k_2 depend from the normalization of the attributes.

3.2.2 System Constraints

This section presents the constraints of the problem, which are common to all objective functions. For the comparison model, where point forecast is used, the constrains are simplified by taking out the s-index and Equation 3.20 is replaced by Equation 3.19.

$$P_{Wi} = P_{Gi} + P_{Pi} \tag{3.19}$$

In classical Wind-Hydro coordination problems, where point forecasting is used, the main constraint is the one which guarantees that the wind power available is either used to pump water into the reservoir or to deliver power directly to the grid (Equation 3.19). Since this dissertation uses multiple short-term wind power scenarios and both P_{Hi} and P_{Gi} are global variables, this constraint would result in a non feasible problem. To suppress this issue an auxiliary variable (d_s) is defined as the difference between the wind power available at that a scenario (P_{Ws}) and the sum of the power delivered directly to the grid (P_{Gi}), the power consumed by the pumping unit (P_{Ps}) and the renewable power wasted in the dumping loads (P_{DLs}), as expressed in 3.1.

$$d_s = P_{Ws,i} - (P_{Gi} + P_{Ps,i} + P_{DLs,i}) \tag{3.20}$$

If the wind energy in a specific wind scenario is less than the energy offered to the market the imbalance will be negative, in the other hand, if it is greater the algorithm will try to avoid the deviation by actioning the pump unit or, as a last resort, by curtailing wind power.

Positive and negative imbalances are taxed differently, so the regulation costs must be define as it was previously define in Equation 3.1, which is a continuous piecewise linear convex function. This convex function can be transformed into an equivalent linear function by expressing in its epigraph form [33], taking the following form:

$$d_{s,i} \cdot (p_i - p_i^+) \leqslant T_{s,i} \tag{3.21}$$

$$-d_{s,i} \cdot (p_i^- - p_i) \leqslant T_{s,i} \tag{3.22}$$

$$T_{s,i} \geqslant 0 \tag{3.23}$$

The regulation costs variable ($T_{s,i}$) acts as a slack variable that, due to constraint 3.23 can take the following values: zero when there is no imbalance, $d_{s,i} \cdot (p_i - p_i^+)$ when the imbalance is positive and $-d_{s,i} \cdot (p_i^- - p_i)$ when it is negative.

As mentioned before, the algorithm defines a pump-unit operation set-point for every wind power scenario, therefore generating a different value of energy stored in the water reservoir for each set-point. Figure 3.6 helps the understanding of this concept by illustrating the daily profile of energy stored in the reservoir in a case study with 30 wind power scenarios, in which every line represents the profile of water stored for a specific scenario.

The amount of water present in the storage unit, $E_{s,i}$, is defined in Equation 3.24, by adding to the value of water present in the previous hour the energy pumped and subtracting the energy generated by the hydroelectric unit. η_P and η_H represent the efficiency of the pump and hydroelectric units, respectively. t is the amount of time that either units are operating, in this dissertation this value is considered constant and $t = 1h$ (the market time interval).

$$E_{s,i} = E_{s,i-1} + t \cdot \left[\eta_P \cdot P_{Ps,i} - \frac{P_{Hi}}{\eta_H} \right] \tag{3.24}$$

Equations 3.25 and 3.26 define the value of water stored in the reservoir at the beginning and end of the day. This detail has relevance because the algorithm performs the optimization for several days in a non continuous way, and this constraint forces a standard initial and final energy levels. Analysing Figure 3.6 it is evident the influence of this constraint.

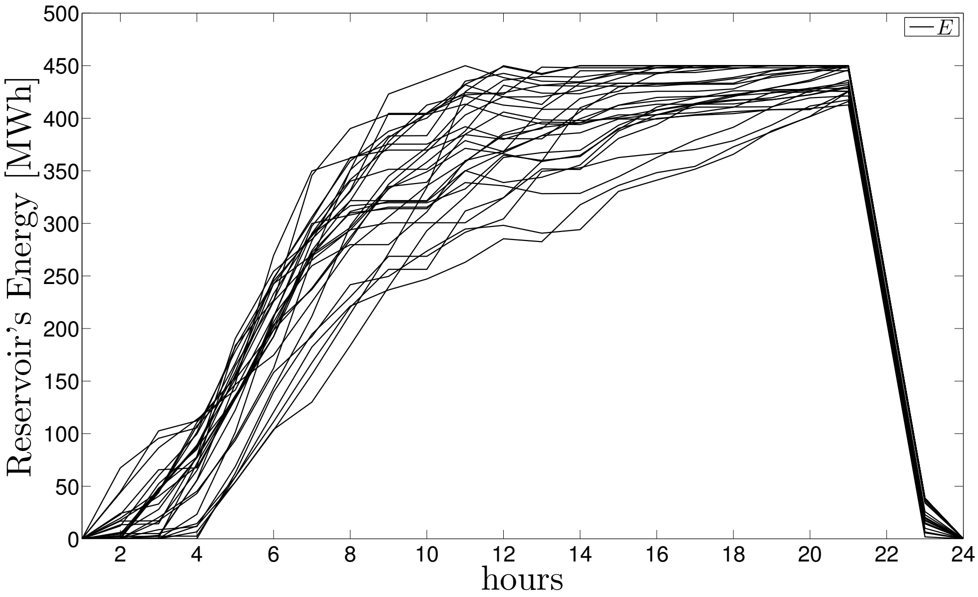

Figure 3.6: Energy Stored in the Reservoir in every hour

$$E_1 = E^{begin} \tag{3.25}$$

$$E_{24} = E^{end} = E^{begin} \tag{3.26}$$

The amount of water available for hydroelectric generation is dependent upon the present level of energy in the reservoir and the pumping power, since it is assumed that the hydro-pump unit is reversible with short commutation time, the system can pump and generate electric energy during the same hourly interval. Equation 3.27 defines that the hydroelectric power (P_{Hi}) cannot be greater than the available energy in the reservoir plus the water pumped in the same period of time. The pumping and hydroelectric power are affected by their efficiency.

$$P_{Hi} \leq \eta_H \cdot \left[\frac{E_{s,i}}{t} + \eta_P \cdot P_{Ps,i} \right] \tag{3.27}$$

$$P_{Ws,i} \leq P_{Gi} + P_{Ps,i} + P_{DL_{s,i}} \tag{3.28}$$

Equations 3.29 - 3.33 represent physical limitations of the variables present in the day-ahead optimization. Equation 3.29 limits the energy stored in the reservoir at its total capacity (E^M). The maximum power output of the pump and hydro units is set by equations 3.30 and 3.31. The wind farm nominal power (P_G^M), sets the boundary of the maximum wind power directly delivered to the grid and the maximum wind power wasted in the dumping loads.

$$0 \leq E_{s,i} \leq E^M \tag{3.29}$$

$$0 \leq P_{Hi} \leq P_H^M \tag{3.30}$$

$$0 \leq P_{Ps,i} \leq P_P^M \tag{3.31}$$

$$0 \leq P_{DL_{s,i}} \leq P_G^M \tag{3.32}$$

$$0 \leq P_{Gi} \leq P_G^M \tag{3.33}$$

3.3 Operational Management Strategy

The stochastic day-ahead optimization results in daily energy bids, which are submitted to the energy market. The high variability of the wind speed and direction leads to uncertainty in wind power forecasting, thus increasing the possibility of imbalances between the contracted and generated energy. The operational management strategy (OS) aims to minimize this deviations, in order to reduce the system's regulation costs.

The OS algorithm performs a new optimization every hour (i, the market time interval) with a sliding window approach and considering all periods from $i = 1$ to $i = n$, using as inputs the past state of the system(e.g. storage level), updated wind power forecasts (WF) and the day-ahead bids. For each hour of the optimization, the inputs are defined as:

- Day-ahead bid: is the bid found by the stochastic DA optimization for the period in question, i.e. $P_{Hi} + P_{Gi}$;

- System's past state: corresponds to the level of energy present in the reservoir in the previous period (E_{i-1}), except for the first hour of optimization, where it is defined as the initial amount of energy present in the reservoir (E^{begin});

- Updated wind power forecasts: are received at each period i and comprehend point predictions from the period i to period $i+4$ (very short-term horizon).

Since the OS algorithm does not use wind power scenarios there is not any scenario-dependent variable, therefore all s-index are removed. The imbalance variable (d_i) is used to account the difference between the contracted energy and the real energy produced by the system. All the other variables have the same significance as in the stochastic DA optimization. In order to differentiate the bids from the stochastic DA optimization from the OS ones, a circumflex accent is added to the DA variables, i.e. $\hat{P}_{Hi}$ and $\hat{P}_{Gi}$.

Figure 3.7 depicts a diagram illustrating the operational management strategy, assuming that updated wind power point forecasts are available every hour for the next 4 hours. Orange arrows represent the day-ahead bids and the blue arrows the updated wind power forecasts.

Considering, for instance, the optimization of the first period ($i = 1$), the algorithm receives as input the bid from the DA algorithm for that period ($P_{H1} + P_{G1}$), updated wind power point forecasts for periods 1 to 5 and the level of energy present in the reservoir (E^{begin}). The optimization is made considering all the periods from 1 to 24, therefore, from period 6 to 24 wind power point forecasts generated for the comparison model of the DA algorithm are used. From the optimization results the real operation points (P_{P1}, P_{H1} and P_{G1}), from which is deduced the energy level in the reservoir at the end of period 1 (E_1). This value is then used as input for the optimization of the next hour, as the system's past state (E_1). This process is repeated until the last period ($i = n = 24$), with all the real operation points known it is possible to calculate the real daily revenue of the system, by multiplying P_H and P_G by the market price and subtracting its regulation costs.

In the end of the operational strategy management the real values of energy generated are known, therefore it is possible to accurately calculate the the real profit of the system.

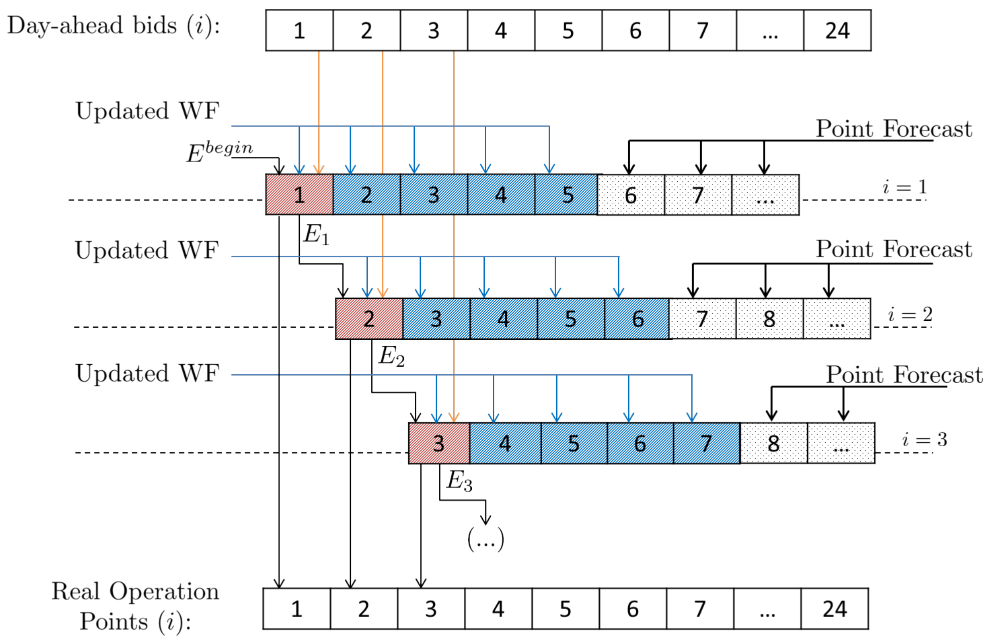

Figure 3.7: Diagram of the rolling window approach of the Operational Strategy algorithm

The objective function of the operational management strategy, Equation 3.34, aims to minimize the absolute value of the imbalances between the energy offered in the day-ahead market and the real energy generated. This formulation can be easily modify to include forecasts for the imbalance prices (if this information is available) Therefore, T_i is a slack variable used to represent the absolute value of the imbalances - Equation 3.35.

$$\min \sum_{i=1}^{n} |T_i| \tag{3.34}$$

$$\text{s.t.} \qquad T_i = \begin{cases} d_i, & \text{if } d_i \geqslant 0 \\ -d_i, & \text{if } d_i < 0 \end{cases} \tag{3.35}$$

Equation 3.35 takes the form of a continuous piecewise linear convex function. To be able use it in a linear programming problem it is necessary to transform it into an equivalent linear function by expressing it as its epigraph form, taking the following formulation:

$$d_i \leqslant T_i \tag{3.36}$$

$$-d_i \leqslant T_i \tag{3.37}$$

$$T_i \geqslant 0 \tag{3.38}$$

As mentioned before, T_i is a slack variable used to find the absolute value of the imbalances.

The imbalances variable (d_i) is define as the difference between the bids made by the stochastic DA algorithm ($\hat{P}_{Hi} + \hat{P}_{Gi}$) and the new operation points defined by the OS optimization ($P_{Hi} + P_{Gi}$) plus the possibility of curtail wind energy (P_{DLi}), as is expressed in Equation 3.39.

$$d_i = \hat{P}_{Hi} + \hat{P}_{Gi} - (P_{Hi} + P_{Gi} + P_{DLi}) \tag{3.39}$$

Equation 3.40 ensures that all wind power available (P_{Wi}) is used, either for pumping purposes (P_{Pi}) or to deliver electric energy directly to the grid (P_{Gi}). If there is an excess of wind energy and the storage unit can not absorb more power, two situation can happen: (a)if the positive imbalance price (p^+) is a positive value, the system chooses to deliver the surplus and pay its regulation costs (b) if $p^+ < 0$ the most advantageous solution is to waste the excess of wind power to the dumping loads (P_{DLi}). The last situation only happens in electric energy market that allow negative prices, such as the Dutch, Nordic or German markets.

$$P_{Wi} = P_{Pi} + P_{Gi} + P_{DLi} \tag{3.40}$$

The constraints presented in Equations 3.41 to 3.49 are similar to the ones used in the stochastic DA optimization, and define the level of energy present in the reservoir (Equation 3.41), the available hydroelectric energy (Equation 3.42), the initial and final levels of energy in the reservoir (Equations 3.43 and 3.44) and the boundaries of the variables used in the optimization (Equations 3.45 to 3.49).

$$E_i = E_{i-1} + t \cdot \left[\eta_P \cdot P_{Pi} - \frac{P_{Hi}}{\eta_H} \right] \tag{3.41}$$

$$P_{Hi} \leq \eta_H \cdot \left[\frac{E_i}{t} + \eta_P \cdot P_{Pi} \right] \tag{3.42}$$

$$E_1 = E^{begin} \tag{3.43}$$

$$E_{24} = E^{end} \tag{3.44}$$

$$0 \leq E_i \leq E^M \tag{3.45}$$

$$0 \leq P_{Hi} \leq P_H^M \tag{3.46}$$

$$0 \leq P_{Pi} \leq P_P^M \tag{3.47}$$

$$0 \leq P_{Gi} \leq P_G^M \tag{3.48}$$

$$0 \leq P_{DL} \leq P_G^M \tag{3.49}$$

3.4 Details about the Computational Implementation

This section addresses the computational off both stochastic day-ahead optimization and operational management strategies.

Both strategies are programmed in Matlab® and take advantage of the algorithm from the Matlab's Optimization Toolbox. In this dissertation the *fmincon* function [34] was used in both strategies, since it can be used for linear and non linear optimization problems.

For the stochastic DA optimization the chosen optimization algorithm was the *interior-point method*, since its characteristics force the algorithm to find the optimal solution by traversing the interior of the feasible region [35][36]. Despite the efficiency, speed and ability to perform well in large-scale problems, several hours were needed to find the optimal solution. To suppress this limitation the gradient (Equation 3.50) and Hessian matrix (Equation 3.51) of the objective function were provided as inputs of the *interior-point* algorithm. These matrices are computed for each objective function of the DA optimization.

$$\nabla f = \begin{bmatrix} \dfrac{\partial f}{\partial P_{Hi}} \\ \dfrac{\partial f}{\partial P_{Ps}} \\ \dfrac{\partial f}{\partial E_s} \\ \dfrac{\partial f}{\partial P_{Gi}} \\ \dfrac{\partial f}{\partial T_s} \\ \dfrac{\partial f}{\partial d_s} \\ \dfrac{\partial f}{\partial P_{DLs}} \end{bmatrix} \tag{3.50}$$

$$H(f) = \begin{bmatrix}
\dfrac{\partial^2 f}{\partial P_{Hi}^2} & \dfrac{\partial^2 f}{\partial P_{Hi}\,\partial P_{Ps}} & \dfrac{\partial^2 f}{\partial P_{Hi}\,\partial E_s} & \dfrac{\partial^2 f}{\partial P_{Hi}\,\partial P_{Gi}} & \dfrac{\partial^2 f}{\partial P_{Hi}\,\partial T_s} & \dfrac{\partial^2 f}{\partial P_{Hi}\,\partial P_{ds}} & \dfrac{\partial^2 f}{\partial P_{Hi}\,\partial P_{DLs}} \\
\dfrac{\partial^2 f}{\partial P_{Ps}\,\partial P_{Hi}} & \dfrac{\partial^2 f}{\partial P_{Ps}^2} & \dfrac{\partial^2 f}{\partial P_{Ps}\,\partial E_s} & \dfrac{\partial^2 f}{\partial P_{Ps}\,\partial P_{Gi}} & \dfrac{\partial^2 f}{\partial P_{Ps}\,\partial T_s} & \dfrac{\partial^2 f}{\partial P_{Ps}\,\partial P_{ds}} & \dfrac{\partial^2 f}{\partial P_{Ps}\,\partial P_{DLs}} \\
\dfrac{\partial^2 f}{\partial E_s\,\partial P_{Hi}} & \dfrac{\partial^2 f}{\partial E_s\,\partial P_{Ps}} & \dfrac{\partial^2 f}{\partial E_s^2} & \dfrac{\partial^2 f}{\partial E_s\,\partial P_{Gi}} & \dfrac{\partial^2 f}{\partial E_s\,\partial T_s} & \dfrac{\partial^2 f}{\partial E_s\,\partial P_{ds}} & \dfrac{\partial^2 f}{\partial E_s\,\partial P_{DLs}} \\
\dfrac{\partial^2 f}{\partial P_{Gi}\,\partial P_{Hi}} & \dfrac{\partial^2 f}{\partial P_{Gi}\,\partial P_{Ps}} & \dfrac{\partial^2 f}{\partial P_{Gi}\,\partial E_s} & \dfrac{\partial^2 f}{\partial P_{Gi}^2} & \dfrac{\partial^2 f}{\partial P_{Gi}\,\partial T_s} & \dfrac{\partial^2 f}{\partial P_{Gi}\,\partial P_{ds}} & \dfrac{\partial^2 f}{\partial P_{Gi}\,\partial P_{DLs}} \\
\dfrac{\partial^2 f}{\partial T_s\,\partial P_{Hi}} & \dfrac{\partial^2 f}{\partial T_s\,\partial P_{Ps}} & \dfrac{\partial^2 f}{\partial T_s\,\partial E_s} & \dfrac{\partial^2 f}{\partial T_s\,\partial P_{Gi}} & \dfrac{\partial^2 f}{\partial T_s^2} & \dfrac{\partial^2 f}{\partial T_s\,\partial P_{ds}} & \dfrac{\partial^2 f}{\partial T_s\,\partial P_{DLs}} \\
\dfrac{\partial^2 f}{\partial d_s\,\partial P_{Hi}} & \dfrac{\partial^2 f}{\partial d_s\,\partial P_{Ps}} & \dfrac{\partial^2 f}{\partial d_s\,\partial E_s} & \dfrac{\partial^2 f}{\partial d_s\,\partial P_{Gi}} & \dfrac{\partial^2 f}{\partial d_s\,\partial T_s} & \dfrac{\partial^2 f}{\partial d_s^2} & \dfrac{\partial^2 f}{\partial d_s\,\partial P_{DLs}} \\
\dfrac{\partial^2 f}{\partial P_{DLs}\,\partial P_{Hi}} & \dfrac{\partial^2 f}{\partial P_{DLs}\,\partial P_{Ps}} & \dfrac{\partial^2 f}{\partial P_{DLs}\,\partial E_s} & \dfrac{\partial^2 f}{\partial P_{DLs}\,\partial P_{Gi}} & \dfrac{\partial^2 f}{\partial P_{DLs}\,\partial T_s} & \dfrac{\partial^2 f}{\partial P_{DLs}\,\partial P_{ds}} & \dfrac{\partial^2 f}{\partial P_{DLs}^2}
\end{bmatrix} \tag{3.51}$$

With the inclusion of the gradient and Hessian matrix, the computation time decreased drastically. For instance, considering a case study with 10 wind power scenarios, the algorithm usually needed around 70 minutes to find the optimal solution for a single day. With these extra inputs, the computational time decreased to around 20 seconds.

The *fmincon* function requires a starting point, if the given point is not inside the bounds of the problem, the software automatically generates a new point inside the variables minimum and maximum limits. To improve the efficiency of the algorithm a preliminary optimization problem is executed to selected a stating point which not only respects the boundaries of the variables, but also all system constraints. The objective function is equal to zero and the constraints of the problem are the same used in the DA optimization. With the use of the starting point determined by the preliminary optimization, the DA optimization requires less iterations and less computational time, which is relevant when hundreds of wind power scenarios are considered.

Chapter 4

Case-Study and Results

This chapter presents and explains the results obtained with the algorithms defined in the previous chapter.

In the first section the characteristics of the hydro-pump-storage system considered for the case-study as well as its assumptions are defined.

The results analysis executed comprehends the stochastic day-ahead optimization with the expected value, unidimensional and multi-attribute objective functions. The deterministic optimization is used as reference, allowing to depict the differences between the optimization considering point forecasting and wind power scenarios. The operational points schedule form the DA optimization are then compared with realized values, obtained from the operational management strategy.

Lastly, it is performed a large scale analysis, where all objective functions are evaluated considering three months of wind and price data.

4.1 Case-Study Description

The case study considered for this dissertation is depicted in Figure 4.1 and consist in a wind farm with total capacity of 246 MW, a reversible hydro-pump station, a water reservoir and dumping loads. Wind power data was collected from the output of 15 hypothetical locations in the state of Illinois in 2006, which were obtained from the National Renewable Energy Laboratory's Eastern Wind Integration and Transmission Study.

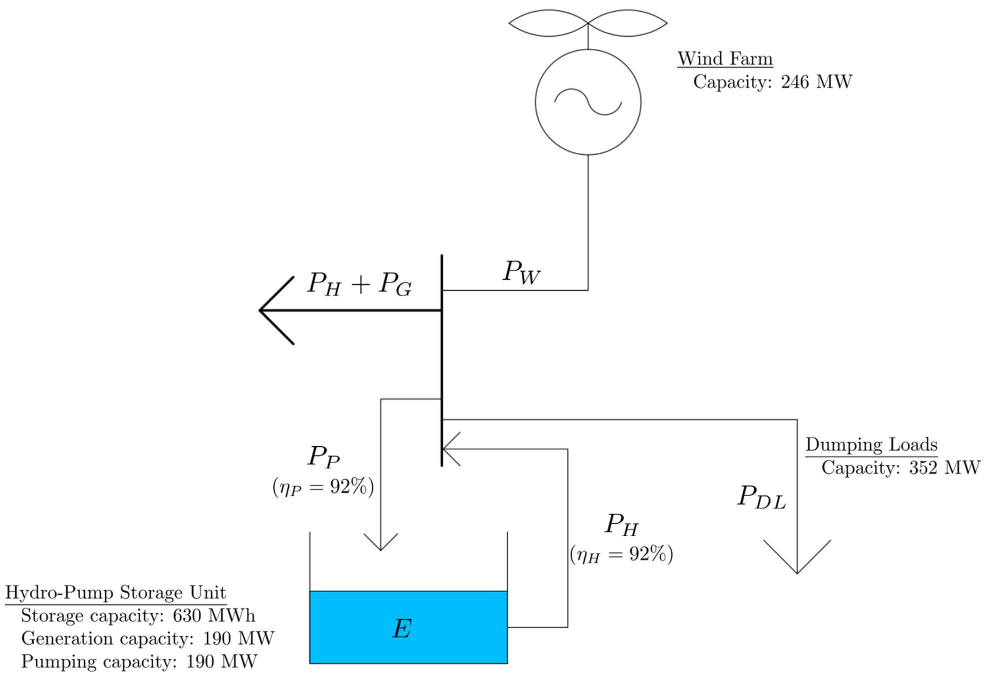

Figure 4.1: System used in the case study

The wind farm can supply directly into the market or partially store their active power into a hydro reservoir, using their pumping capacity. The hydroelectric unit can generate active power from the previously pumped stored wind energy. It is assumed that all elements in the system are connected to a single node of the transmission system. The possibility of congestion in the transmission lines and the losses from the power flows are neglected.

Wind power short-term scenarios were obtained using the method proposed by Pinson *et al.*[12] and described in Section 2.2.2 for the stochastic day-ahead algorithm and for the operational management strategy updated wind point forecasts were obtained from an auto-regression model of second order.

It is assumed that the reversible hydro-pump station has equal characteristics for generation and pumping purposes, with a power of 190 MW and an efficiency of 92%. The possibility of alternately perform both pumping and generation operation during the same hour is considered. Operationally, there is a switch time between the pumping and generation activities, but in this case study this time gap is neglected. Both pumping operation and maintenance costs are not considered, as well as hydro generating costs.

The storage capacity of the hydro reservoir (125,200 MWh) is very high, but it is assumed that this capacity is not fully available for compensation activities. In the present case, a storage capacity of 630 MWh is considered, which is approximately equivalent to 3 hours of hydroelectric generation at nominal power. The possibility of a natural water inflow in the reservoir is ignored.

In this work, the dumping loads are used to simulate the curtail of wind power. They have the same capacity as the wind farm's nominal power, therefore are able to absorb all wind power in an extreme situation.

The market and imbalance prices considered are real and from the Iberian and Nordic electricity markets and from 2013. The wind power data used in this case study date from October 2006 to 31 December 2006. Even though that the prices and wind data do not overlap in time, in this case-study it is assumed that both wind and prices data date from October to December of the same year.

4.2 Illustrative Example

This section aims to explain the operation of the stochastic day-ahead optimization and the operational management for a typical day, considering the expected value objective function. In order to simplify the graphical representation of the results, only 10 wind power scenarios are used as input.

4.2.1 Day-ahead Strategy

Figure 4.2 illustrates the 10 short-term wind power scenarios (WP Scenarios) considered as input in the stochastic day-ahead optimization of the present case. The market and imbalance prices used are represented graphically in Figure 4.3. Market prices are from the day-ahead market, thus in some cases it crosses with the regulation prices.

The day in question is characterized by low market prices from 2 AM to 7 AM, with a minimum of 29 EUR/MWh, and for the rest of the day the prices stabilized between 38 EUR/MWh and 53 EUR/MWh until the peak hours (19h - 23h) where the price reaches its maximum of 85 EUR/MWh (20h).

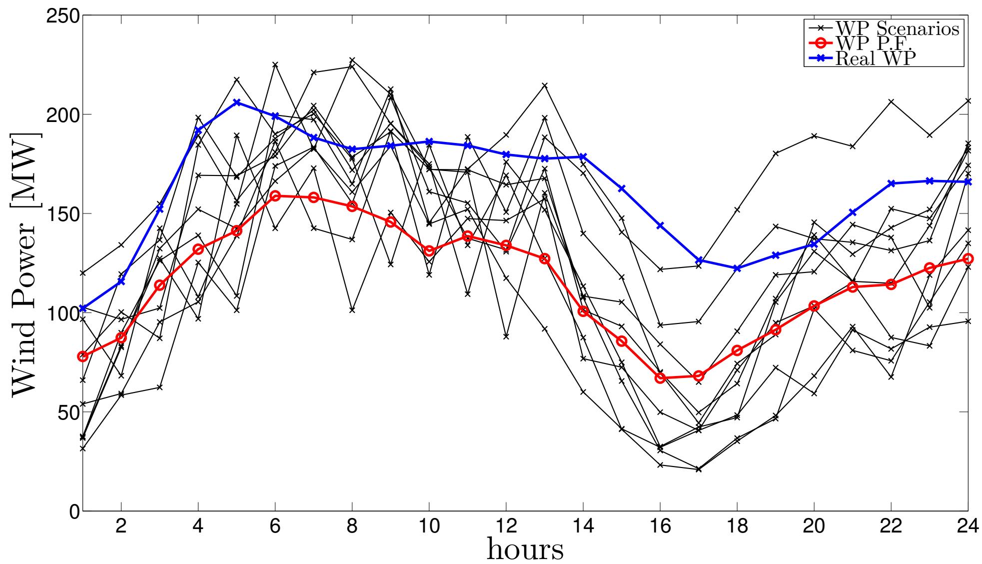

Figure 4.2: Wind power scenarios, point forecasts and real wind power considered

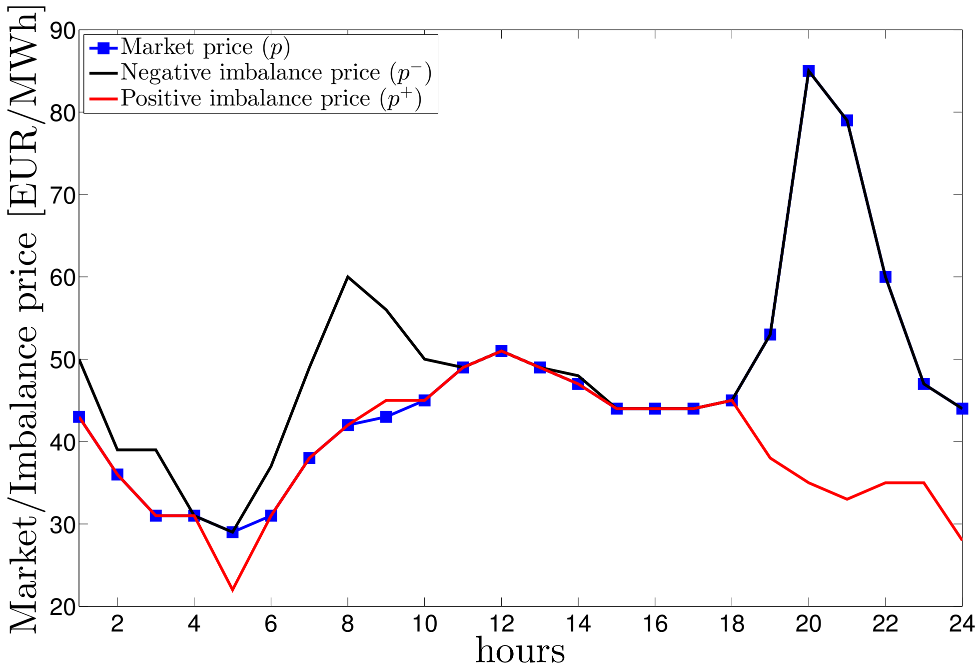

Figure 4.3: Market and imbalance prices

In the day-ahead stochastic optimization, the hydro-pump station aims to increase the system revenue by performing price arbitrage. Given the typical nature of the spot market prices, where lower prices at the beginning of the day are expected, it is more profitable to pump water into the reservoir at this period and deliver energy at peak hours, where the price is usually higher.

Figure 4.4 represents the hydroelectric power (P_H) scheduled for the day ahead, determined by the algorithm in question. As the figure shows the hydroelectric operation is highly correlated to market prices, with generation at the period with higher prices (20h-22h).

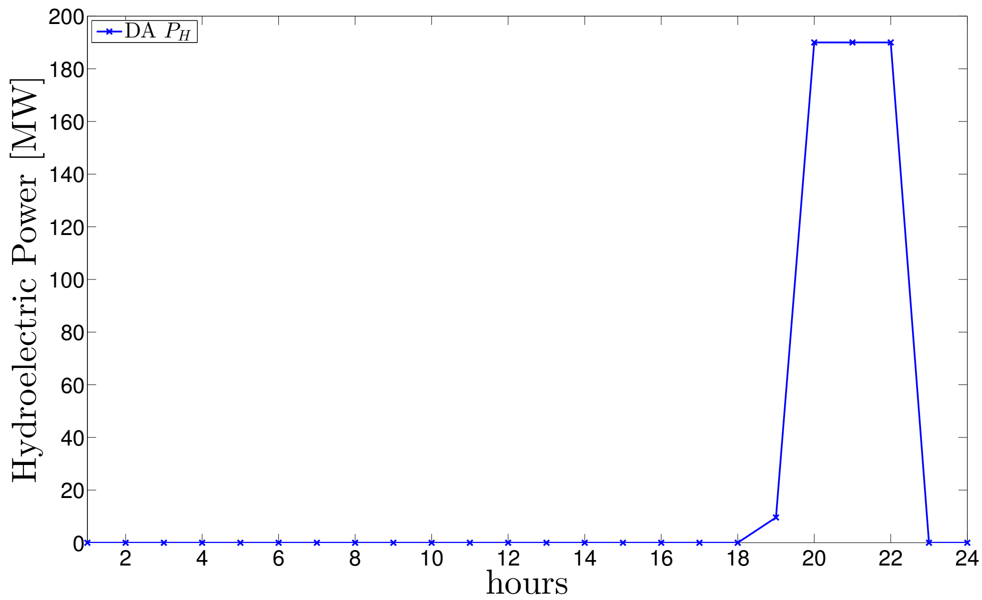

Figure 4.4: Hydroelectric power defined by the stochastic day-ahead optimization

Figure 4.5 demonstrates the pumping power (P_P) for each wind power scenario. In the first hours of the day, where market prices are lower, all pumping scenarios are active and operating near their nominal value.

The electric energy stored in the reservoir (E) at the end of the day is fixed in a predefined value and the P_H is common to all scenarios. Therefore the E at the beginning of 22h (last hour where hydroelectric energy is generated) must be the same at all scenarios, so that a single value of P_H results in the emptying of all E scenarios. The algorithm uses the pumping power to fulfil this constraint, hence the existing of P_P in some scenarios at a less favourable period (8h).

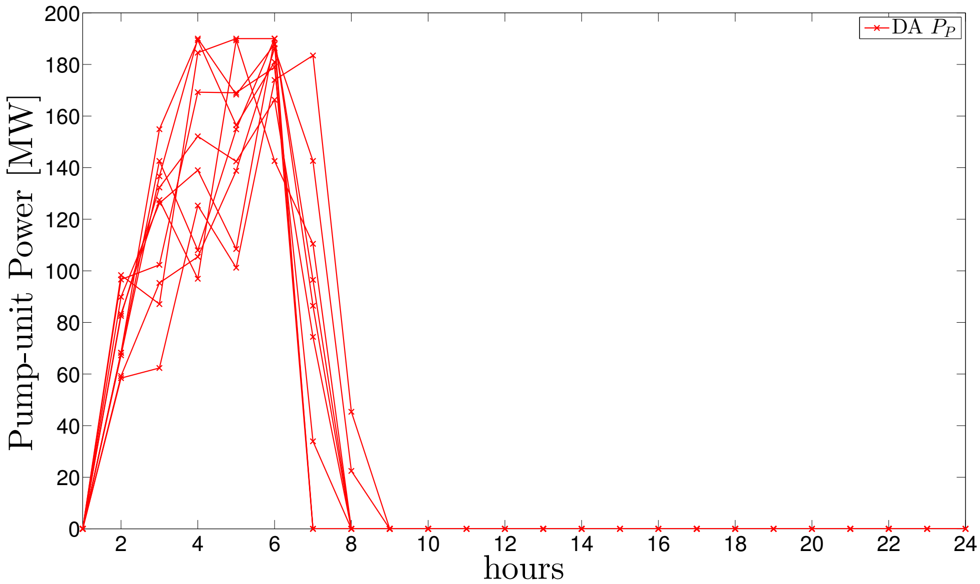

Figure 4.5: pump-unit power defined by the stochastic day-ahead optimization

The energy stored in the reservoir depends of P_H and P_P, thus it is relevant to evaluate the three variables as a whole. Figure 4.6 represents the hydro-pump storage coordination, where it is possible to observe the filling of the reservoir (pumping) at the first hours of the day and its emptying (generating) at peak hours. As the figure shows, the initial and final levels of the reservoir are the same.

Since the wind power available (P_W) in each scenario is divided into P_P (scenario-dependent) and P_G (global variable), the amount of energy stored in the water reservoir varies according to the P_W. Thus the discrepancy of E throughout the day.

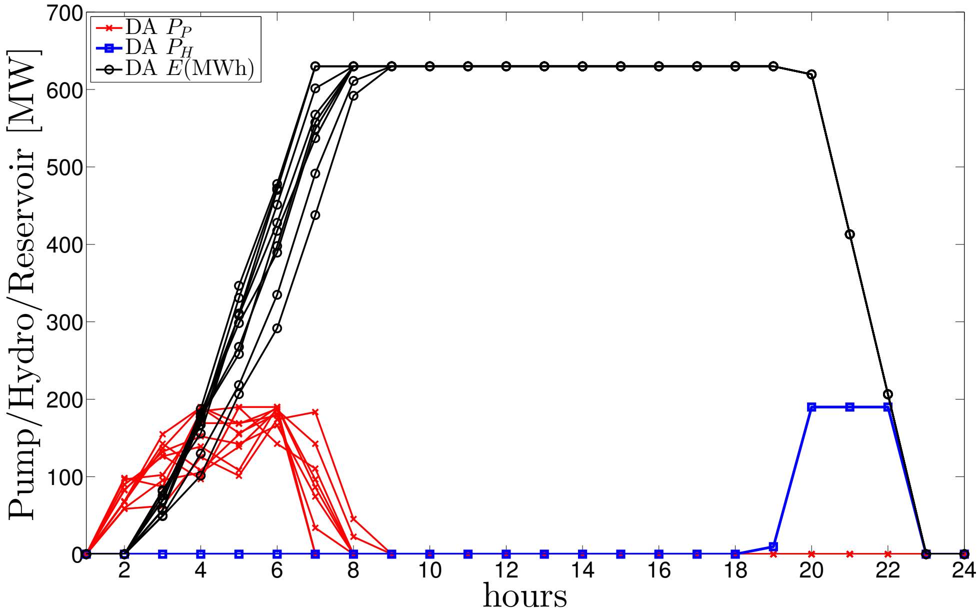

Figure 4.6: Operation of the hydro-pump storage unit defined by the stochastic day-ahead optimization

Figures 4.7 and 4.8 represent the schedule wind power directly delivered to the grid (P_G) for the day ahead. Since this variable is common to all scenarios, the algorithm has to take in account all pumping and wind power scenarios, in order to minimize the regulation costs.

To understand the choices made by the optimization problem for the wind power directly delivered to the grid and its imbalances it is crucial to understand how the objective function calculates the expected profit of the system.

The objective function presented in Section 3.2.1, is divided into two terms: revenue and costs of the system. Since P_G and P_H are global variables and the operational costs of the hydro-pump unit are not considered it is the wind power imbalance (d) and its regulation costs (T) that dictate the profitability of the scenario.

If d is a positive value, i.e. the scenario delivers more wind power than the proposed bid to the market, the system is remunerated at market price for the surplus and its regulation costs are deducted. In other words, the extra energy delivered to the system will be remunerated at $d \cdot p_i - d \cdot (p_i - p_i^+)$. Therefore, with $d > 0$, three situations can occur:

- $\mathbf{p_i^+} < \mathbf{p_i}$, this is the most usual situation, in which the system operator has the surplus of power delivered remunerated at a lower price than the market spot price.

- $\mathbf{p_i^+} = \mathbf{p_i}$, in this situation the surplus and bid remuneration are equal;

- $\mathbf{p_i^+} > \mathbf{p_i}$, this is the most advantageous situation for the system, since the surplus is remunerated at a higher price than the bid.

In the first situation the algorithm aims to minimize the imbalance in order to avoid regulation costs. But in the other two situations, and considering $T \geqslant 0$, the algorithm has no incentive to reduced the imbalance, since it is remunerated at the same value than the market spot price. Furthermore, since the reduction of the imbalance is obtain by increasing the bid to the market it could lead to negative imbalances in scenarios with less wind power. Therefore, in this situations, the P_G bid proposed to the electricity market is small as it is depicted by Figure 4.7. The shaded periods represent the hours where $p_i^+ = p_i$, in which is clear that the algorithm chooses to schedule P_G as low as possible.

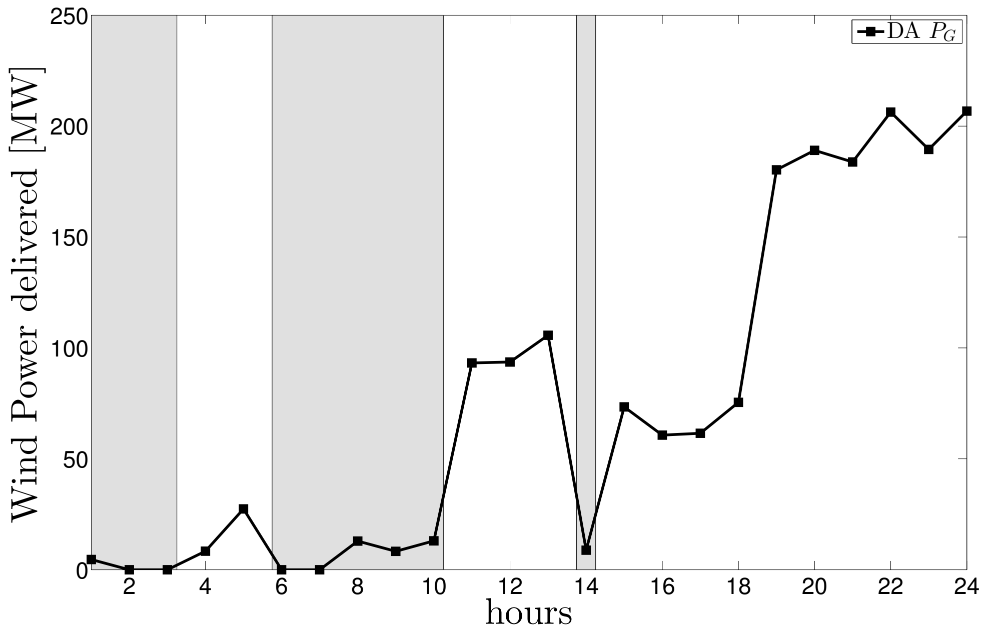

Figure 4.7: Wind power delivered directly to the grid

Alternatively if d is negative, i.e. the scenario is unable to fulfil the proposed bid, the lacking amount is deducted at market price plus its regulation costs, i.e. $-d \cdot p_i - d \cdot (p_i^- - p_i)$. With the negative imbalances three situations can happen:

- $\mathbf{p_i^-} > \mathbf{p_i}$, this is the most usual situation, in which the system operator has to pay the energy imbalance at a higher price than the market spot price;

- $\mathbf{p_i^-} = \mathbf{p_i}$, in this situation the deficit of energy is paid at market price;

- $\mathbf{p_i^-} < \mathbf{p_i}$, this is the most advantageous situation for the system, since, despite the deficit of energy, the system receives an extra remuneration.

The algorithm aims to avoid situations where regulation costs have to be paid, but when the imbalance incurs in a null regulation cost the algorithm will prioritize the scenario with more wind power, resulting in P_G values higher than expected. Figure 4.8 allows the visualization of this method, where the algorithm defines P_G as the maximum wind power available of all scenarios when $p_i^- = p_i$ (shaded areas). At 5h, the P_G bid is small, because most of the wind power is used to pump water into the reservoir.

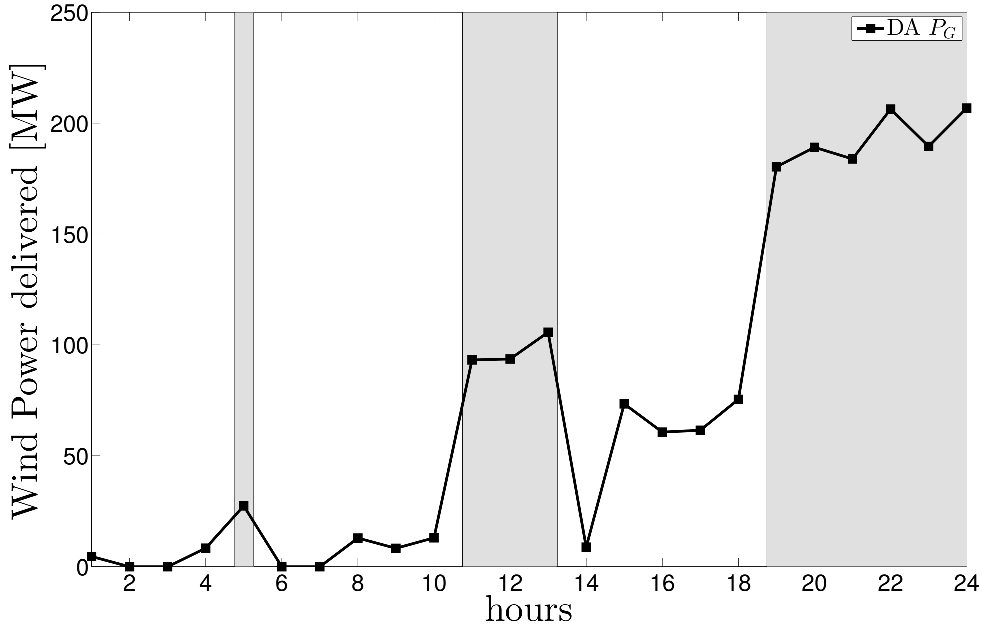

Figure 4.8: Wind power delivered directly to the grid

In conclusion, when the power imbalance favours the system the regulation costs are eliminated [37], therefore the algorithm takes extreme choices in order to reduce risk.

Figures 4.9 and 4.10 illustrate the power imbalances (d) for each scenario. The first figure highlights the periods where positive imbalances favour the system and the second enhances the hours when it is the negative imbalances that have no regulation cost.

When there are no positive regulation costs, every d works like a scenario-dependent P_G, since the surplus of wind power is remunerated at market price. Hence the higher amount of positive imbalances at those periods.

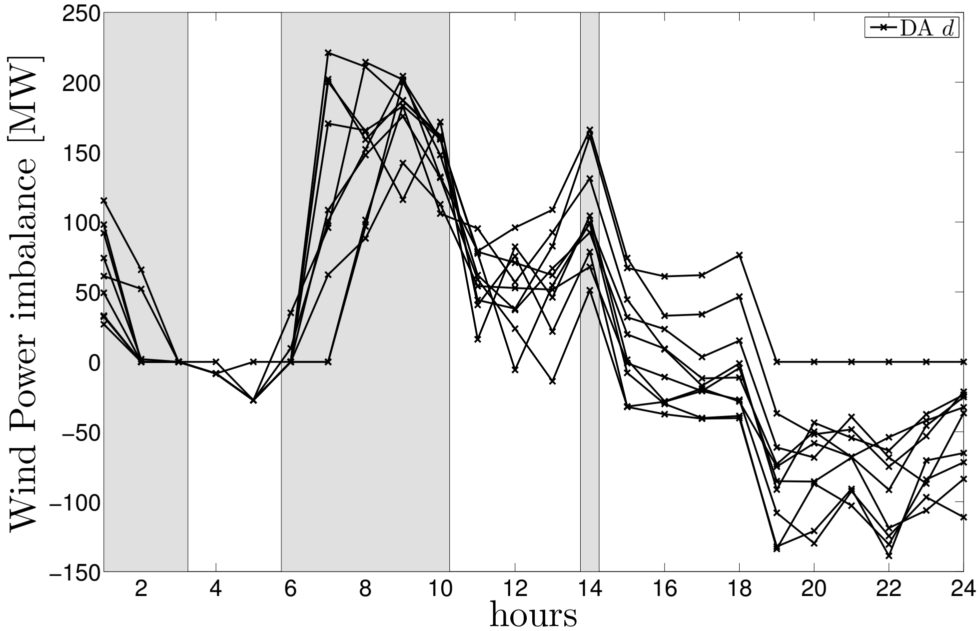

Figure 4.9: Wind power imbalances resulting from the stochastic day-ahead optimization

However, when there are no negative regulation costs it is the opposite that happens. From 19h until the end of the day is clear that the algorithm sets the higher wind power scenario as reference for the wind power bid, and since the other scenarios have less wind power available d assumes considerable values. From 11h to 13h both p^+ and p^- are equal to p_i, hence most of deviations are positive.

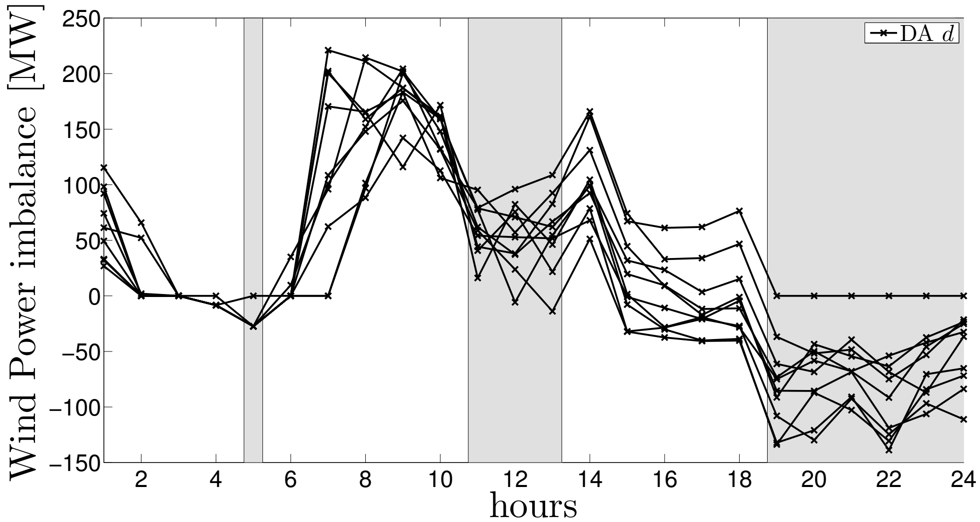

Figure 4.10: Wind power imbalances resulting from the stochastic day-ahead optimization

Figure 4.11 represents the consequence of the power imbalances presented before. Despite the presence of substantial d, the algorithm manages to suppress all expected regulation costs. In fact, at 9h is expected that the system will receive an extra remuneration for its surplus of wind power delivered, since $p_9^+ > p_9$.

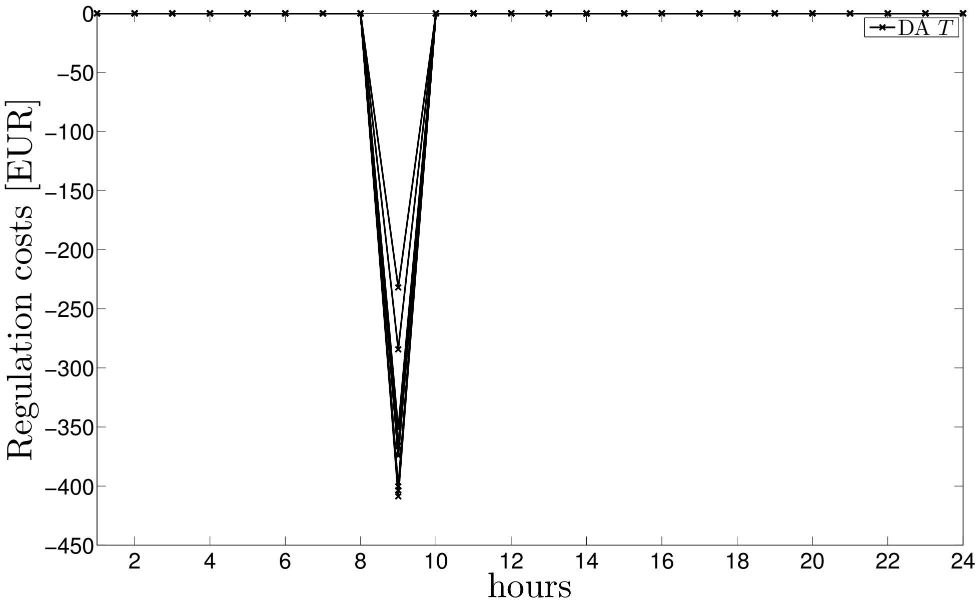

Figure 4.11: Regulation costs resulting from the stochastic day-ahead optimization

4.2.2 Operational Strategy

The stochastic day-ahead optimization schedules the bids proposed to the electricity market. In this section those bids, and respectively variables, are compared with the real operation points obtained with the operational management strategy.

This analysis aims to evaluate the efficiency of the DA optimization and understand if the operational management strategy is able to successfully minimize the impact of the power imbalances caused by the wind power uncertainty.

Figure 4.2 illustrates the wind power scenarios considered as input for the DA optimization as well as the real wind power measured.

A comparison between DA schedule and the real hydroelectric power (P_H) generated is shown in Figure 4.12. Both operations follow a similar pattern, with the the only difference is that the operational management strategy is forced to start generating electric energy an hour earlier, to suppress a wind power deficit.

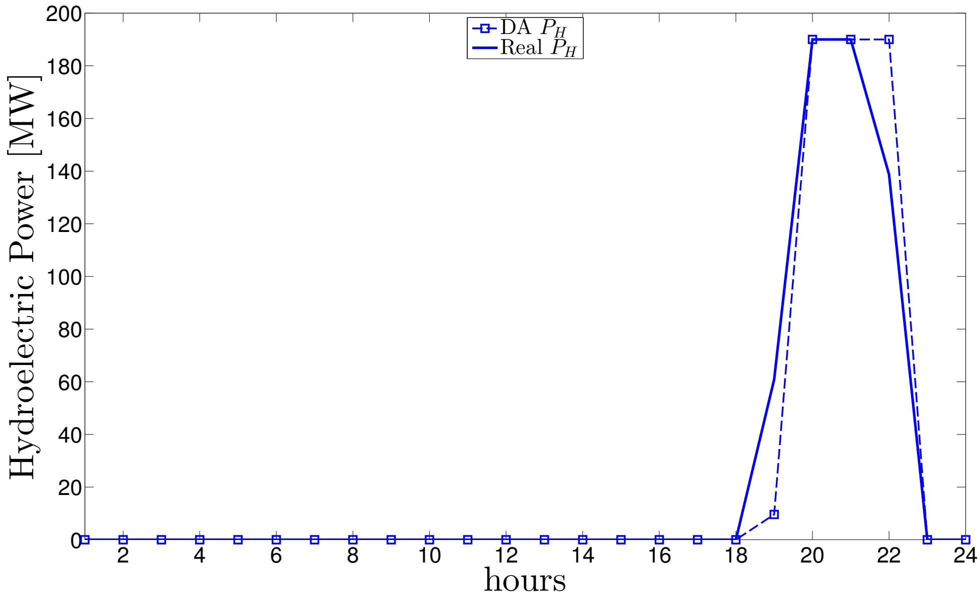

Figure 4.12: Comparison between DA and real hydroelectric power (P_H)

Figure 4.13 points out the comparison between the operation points determined by the stochastic DA optimization and the ones determined by the operational management strategy.

The only difference between he strategy outlined by the stochastic DA optimization and the real operation is that due to the low P_G bid the algorithm is forced to deviate the excess of wind power to the pump-unit, thus starting it an hour earlier than scheduled.

It is interesting to denote the similar operation pattern of the P_P from both algorithms, despite the inconsideration of market and imbalance prices from the operational management strategy.

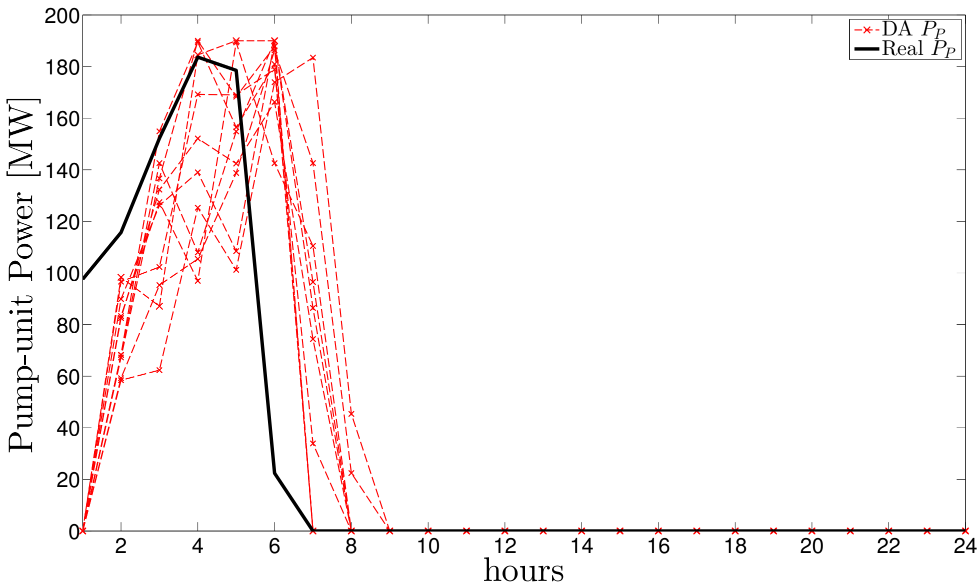

Figure 4.13: Comparison between DA and real pumping power (P_P)

From the analysis of Figure 4.14 one can conclude that the real wind power delivered is unquestionable different from the bid schedule.

From 6h to 18h the real P_G is greater than the bid, consequence of the equality between market and positive imbalance prices.

From 19h until the end of the day, period where $p_i = p_i^-$, the real P_G is lower than the bid. The DA stochastic algorithm, knowing that there are no negative regulation costs, defines the market bid as the maximum wind power scenario available. Since the real wind power is lower, the system operator has a lower revenue than expected.

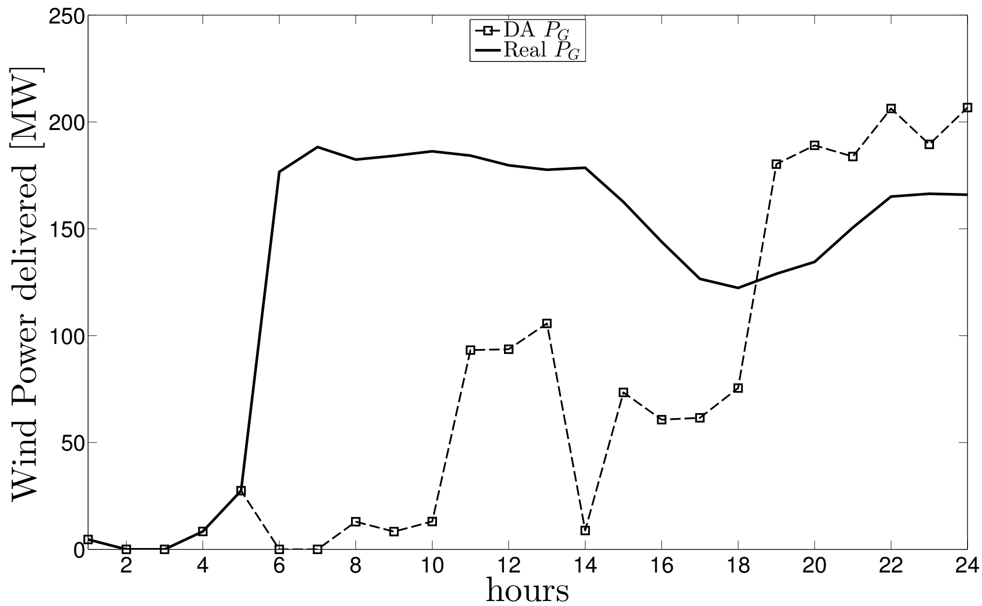

Figure 4.14: Comparison between DA and real wind power directly delivered to the grid (P_G)

Figure 4.15 allows the visualization of the pump/hydroelectric power and the energy stored in the water reservoir. Displayed in bold are the operation points defined by the operational management strategy.

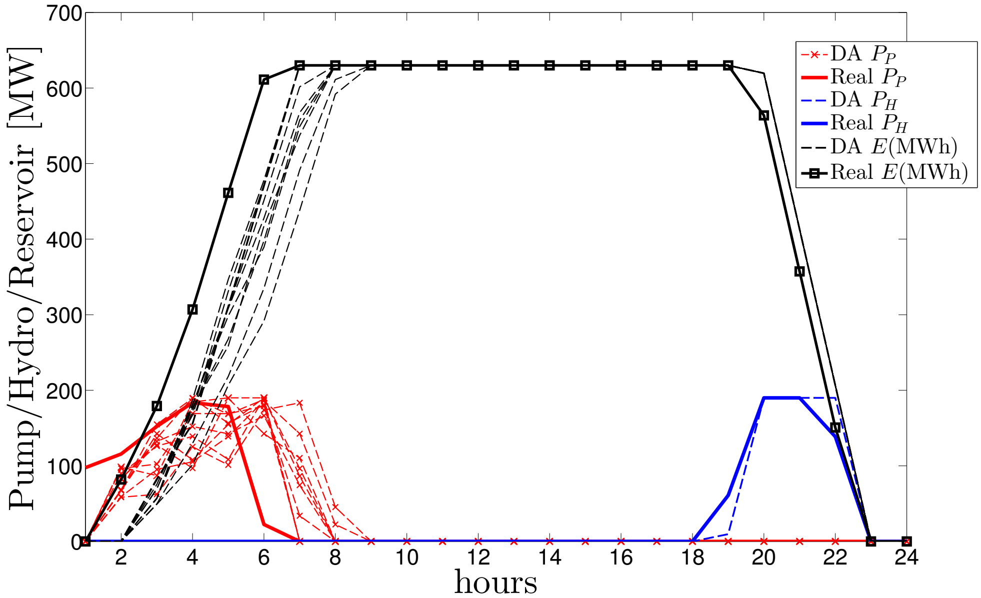

Figure 4.15: Comparison between DA and real operation of the hydro-pump storage unit

Figures 4.16 and 4.17 show the power imbalances and its regulation costs, respectively, for both algorithms considered in this dissertation. The DA d are only related to wind power imbalances, but he Real d represents the difference between the bid proposed to the electricity market $(\hat{P_H} + \hat{P_G})$ and the real electric energy generated $(P_H + P_G)$.

The real power imbalances follow the pattern defined by the DA d. Given the characteristic of the imbalance and market prices for this day, the positive imbalances do not represent loss for the system, in contrast, the negative imbalances present in the finals hours of the optimization period reduce the system profit.

The coordination between the DA stochastic optimization and the operational management strategy was able to not only eliminate regulation costs but also receive a small remuneration for the electric energy surplus at 9h, when the positive imbalance price is higher than the market price.

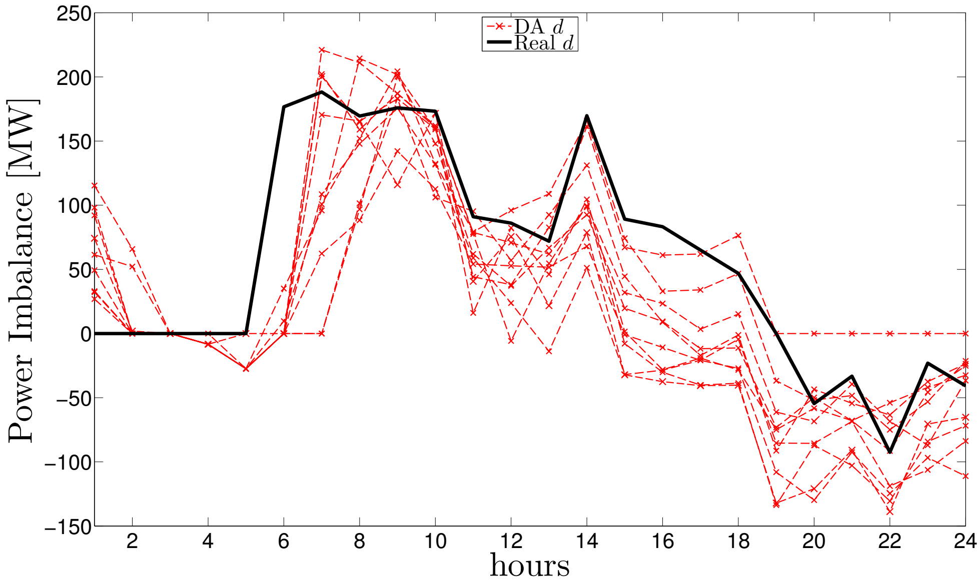

Figure 4.16: Comparison between DA and real power imbalances (d)

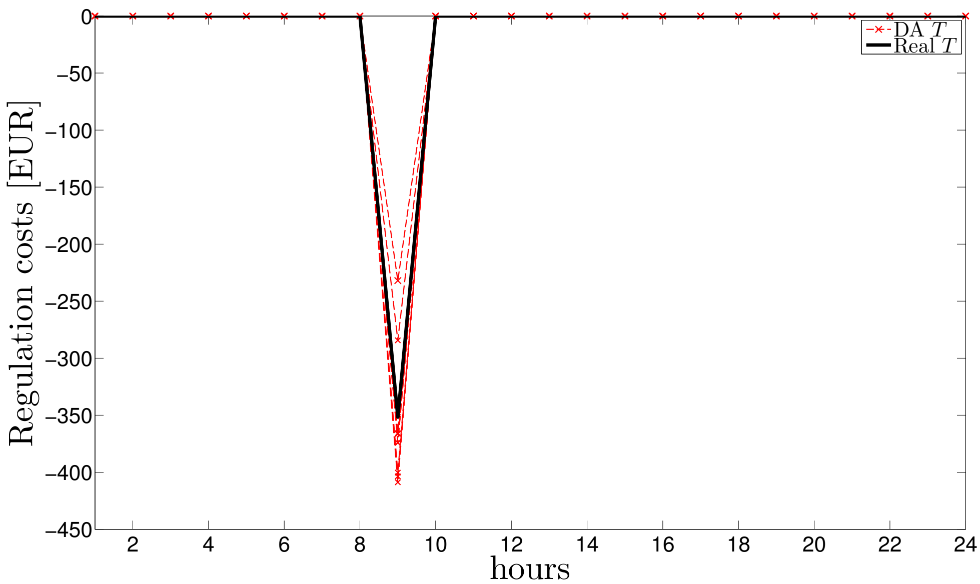

Figure 4.17: Comparison between DA and real regulation costs (T)

4.2.3 Comparison between Point Forecast and Wind Power Scenarios

This section compares the results of performing the stochastic day-ahead optimization and the operational management strategy using two different methods of wind power forecasting: point forecasting and wind power short-term scenarios.

Given the characteristics of point predictions, the DA optimization, using this method of forecast as input, does not lead to imbalances or regulation costs.

Figure 4.2 illustrates the wind power scenarios and point forecasts used for the DA optimization and the real wind power measured in the day considered, which reveals a measure wind power greater than the point forecasts predictions.

To improve the interpretation of all figures presented in this section, the colour characterization described in Table 4.1 is established.

Table 4.1: Colour characterization of the data series

Day-ahead optimization - WP Scenarios	Grey
Operational management strategy - WP Scenarios	Black
Day-ahead optimization - Point Forecast	Orange
Operational management strategy - Point Forecast	Red

Figure 4.18 depicts a comparison between the hydroelectric power schedule with point forecasting and with short-term scenarios.

For both forecasting methods, the real hydroelectric generation is perform mainly between 20h and 22h. From 20h to 22h the real P_H with P.F. is less than the schedule value, this happens because there is more wind power than predicted, forcing the operational management strategy to curtail the hydroelectric power. With the point forecasting there is a peak in the last hour of the optimization, which occurs with the purpose of emptying the storage unit, since reservoir's energy level at the last hour must be equal to a predefined value.

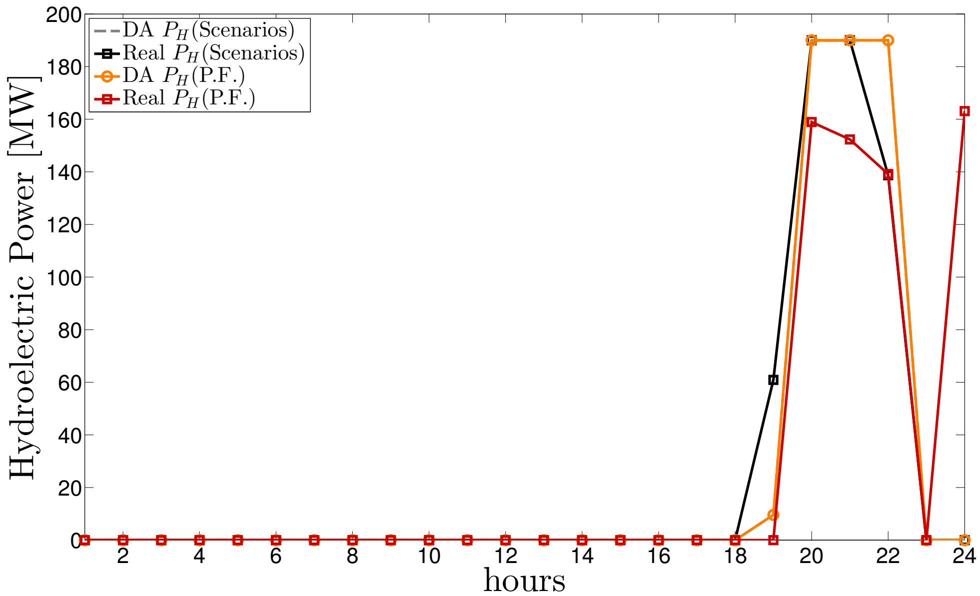

Figure 4.18: Hydroelectric power - comparison between PF and WP scenarios

From the analysis of Figure 4.19, where P_G considering both algorithms and forecasting methods is shown, one can conclude that both forecasting methods result in similar P_G values, despite having different P_G bids.

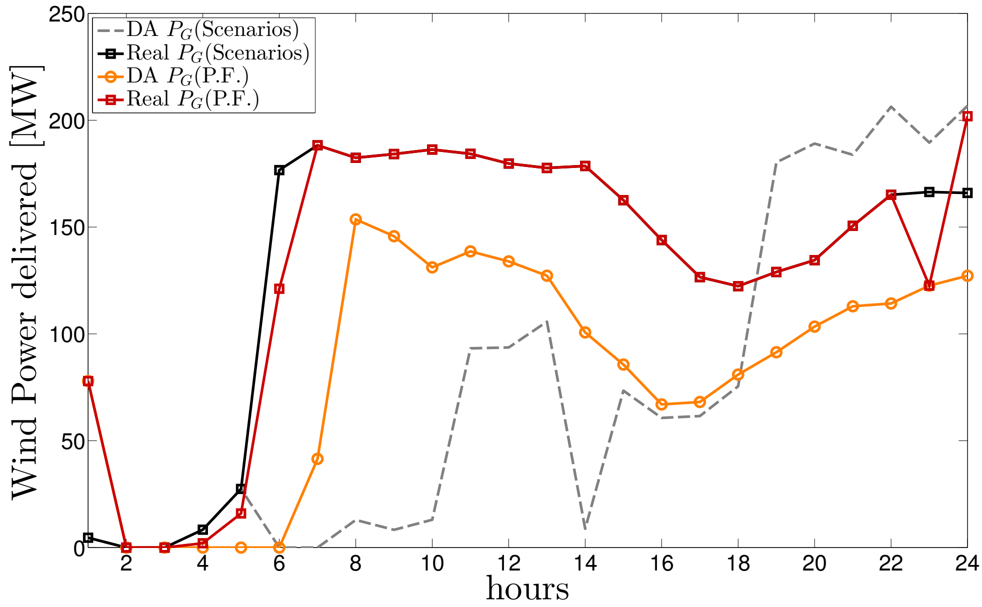

Figure 4.19: Wind power directly delivered to the grid - comparison between PF and WP scenarios

The comparison between pump-unit power determined with point forecasting and with short-term scenarios, described in Figure 4.20, shows that the algorithms, when considering point forecasts, choose to pump water into the reservoir in the first hours of the day. Additionally, since the pump-unit is operating a full or near full capacity, the reservoir will reach its maximum capacity early, hence preventing P_P to operate throughout the rest of the day.

At 23h the pump-unit is active for the P.F. optimization in order to suppress the surplus of wind power.

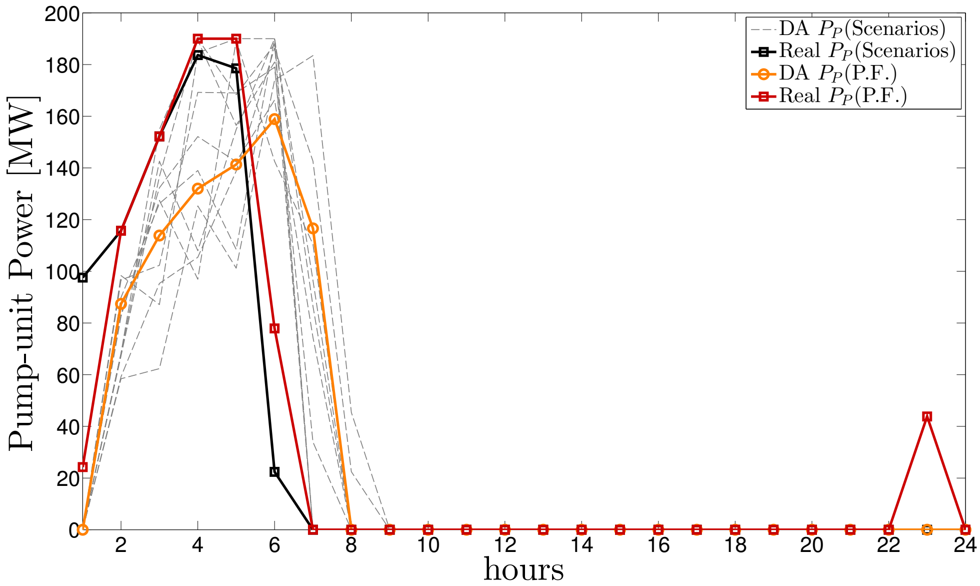

Figure 4.20: Pump-unit power - comparison between PF and WP scenarios

With the reservoir reaching its maximum capacity early in the day (Figure 4.21), and, since P_H only stars generating between 19h and 20h, there is a 12 hour period in which is not possible to use the pump-unit station to suppress positive imbalances.

Since the real wind power revealed to be higher that the point predictions, therefore neglecting the need to use P_H to suppress shortness of power, the level of energy stored in the reservoir considering both algorithms with P.F. is almost identical. The biggest difference occurs in the last hours, where the reservoir's energy level reduces slowly than predicted, since the hydroelectric power is reduced to suppress positive imbalances.

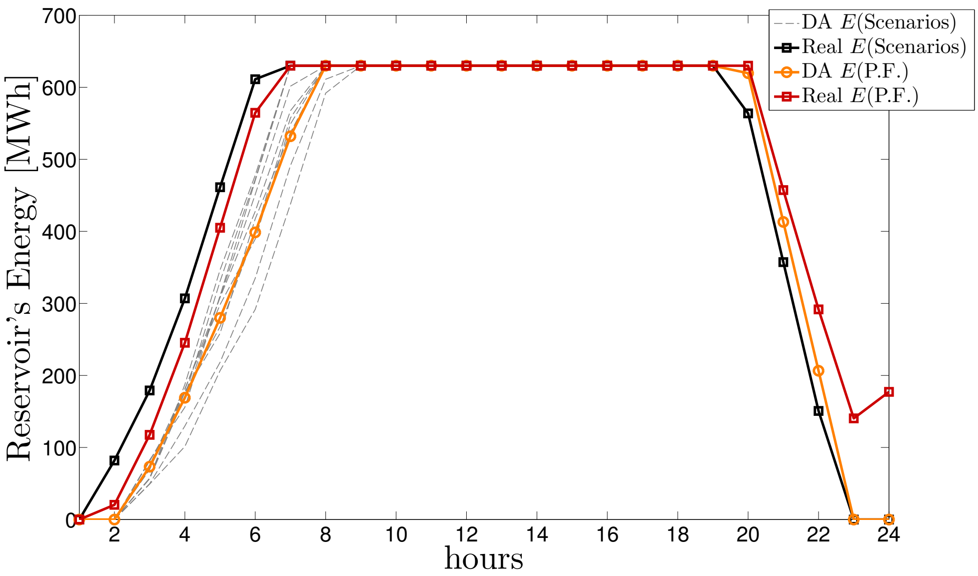

Figure 4.21: Energy stored in the reservoir - comparison between PF and WP scenarios

Figure 4.22 compares the imbalances considering both algorithms and both forecasting methods. Contrary to the wind power scenarios the P.F. algorithm is able to avoid negative imbalances throughout the day. The positive imbalance at 24h results from the necessity of emptying the water reservoir, thus using the hydroelectric generating unit.

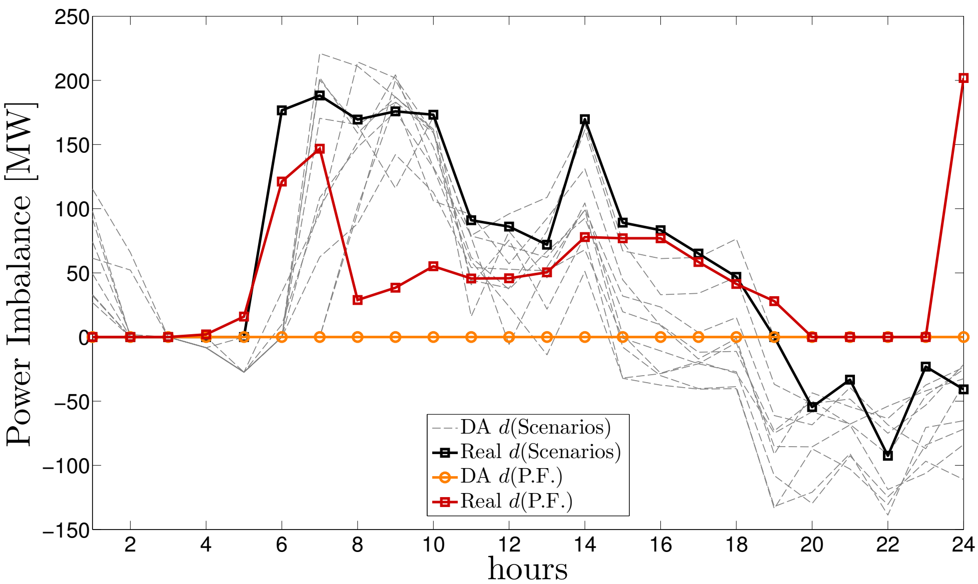

Figure 4.22: Wind power imbalances- comparison between PF and WP scenarios

Figure 4.23 depicts the regulation costs which result from the power imbalances. The operational management strategy is able to minimize the point forecast T until the last hour. Nevertheless is more profitable to pay the regulation cost associated with the surplus of electric energy than to curtail it.

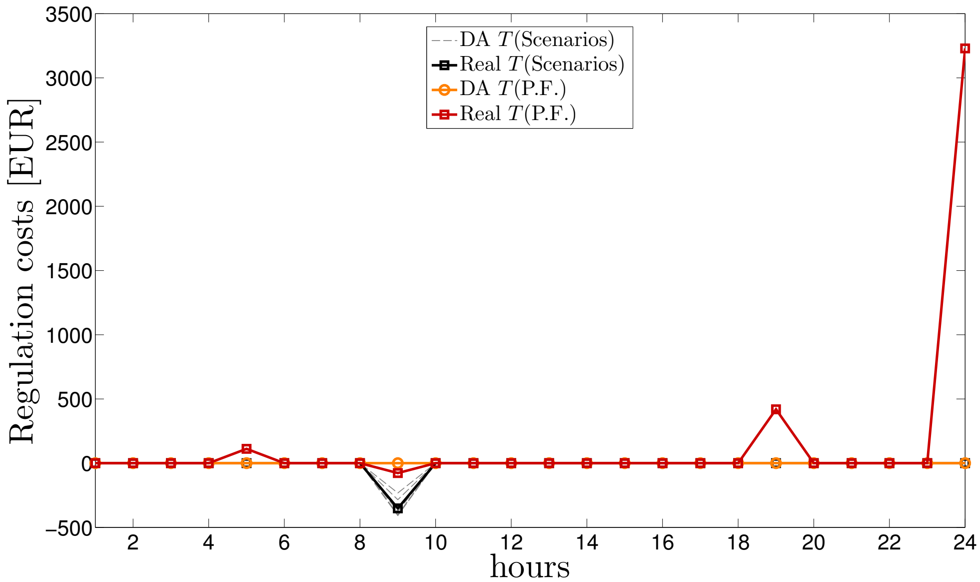

Figure 4.23: Regulation costs - comparison between PF and WP scenarios

Table 4.2 discloses the day-ahead bid revenue,earnings from the surplus generation, regulation costs and the total profit of the system, which is the sum of the day-ahead and surplus revenue minus the regulation costs. For the day evaluated, the use of wind power scenarios shows more profitable than point forecasting.

Since the operational management strategy performed accordingly with both forecasting methods, one can conclude that it is in the optimization of the bids proposed to the energy market that lays the key to improve the profit of the hydro-pump storage coordination.

The consideration of imbalance prices in the DA optimization proved to be advantageous, because allowed the algorithm to choose the bid proposed to the electricity market in a way that avoided all regulation costs.

Figure 4.24 discloses the profit of the system throughout the day. As expected the profit is greater at peak hours.

From 19h to 21h the stochastic optimization, knowing that there would be no regulation cost for delivering less power than the contracted bid, is able to deliver all wind power available, making use of its massive P_G bid and achieving more profit than the point forecast optimization.

Despite the regulation costs paid by the PF optimization at 24h it was able to obtain a larger profit, but not sufficient to suppress the profit opportunity missed in the previous hours.

Table 4.2: Profit of the system - comparison between PF and WP scenarios

	WP Scenarios	Point Forecast
Day-ahead bid	127,580 EUR	146,900 EUR
Bid diff	70,014 EUR	47,470 EUR
Regulation costs	-351 EUR	3683 EUR
Profit	197,945 EUR	190,690 EUR

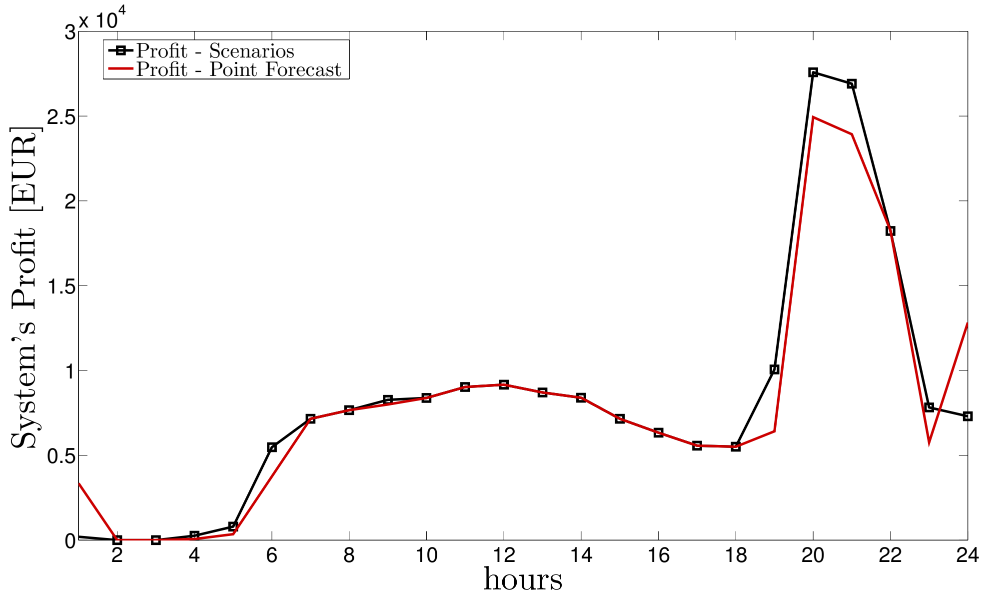

Figure 4.24: Profit of the system- comparison between PF and WP scenarios

4.2.4 Unidimensional Utility Function - Risk Averse vs Risk Prone

In this section the unidimensional expected utility (Section 3.2.1) is used to compare the day-ahead optimization results between two decision makers with different attitudes toward risk: one averse and the other prone. The attitude towards risk is modelled based on the β coefficient. In this case-study the DM with aversion to risk has $\beta = -3$ and the DM prone to risk has $\beta = 3$.

In order to enhance the analysis, the decision maker averse to risk has its variables illustrated in blue and the prone to risk illustrated in red.

Figure 4.25 shows the hydroelectric power schedule for the day-ahead considering the two different attitudes towards risk. Provided that the DM's attitude do not drastically affect the amount of energy stored, and since the generating unit is mainly used as a price arbitrage tool, both averse and prone strategies should be identical, as the graphical representation shows.

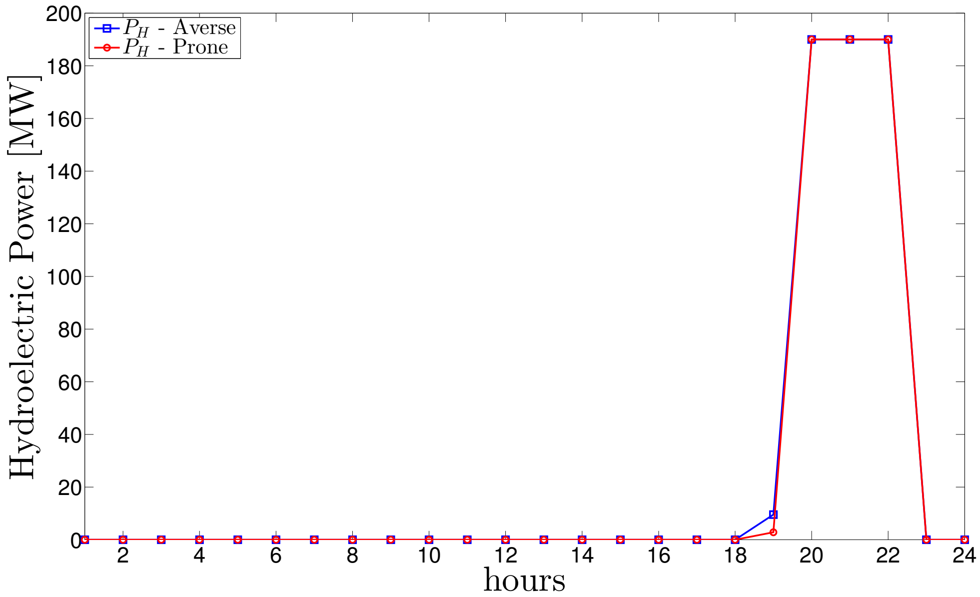

Figure 4.25: Hydroelectric power - risk averse and risk prone

Interpreting Figure 4.26, which represents the pump-unit power for both attitudes of the decision maker, one can verify that the main different happens in the optimization of the averse DM. At 15h and 16h the algorithm has to pump water at a disadvantageous period in order to level the reservoir's energy in 3 scenarios.

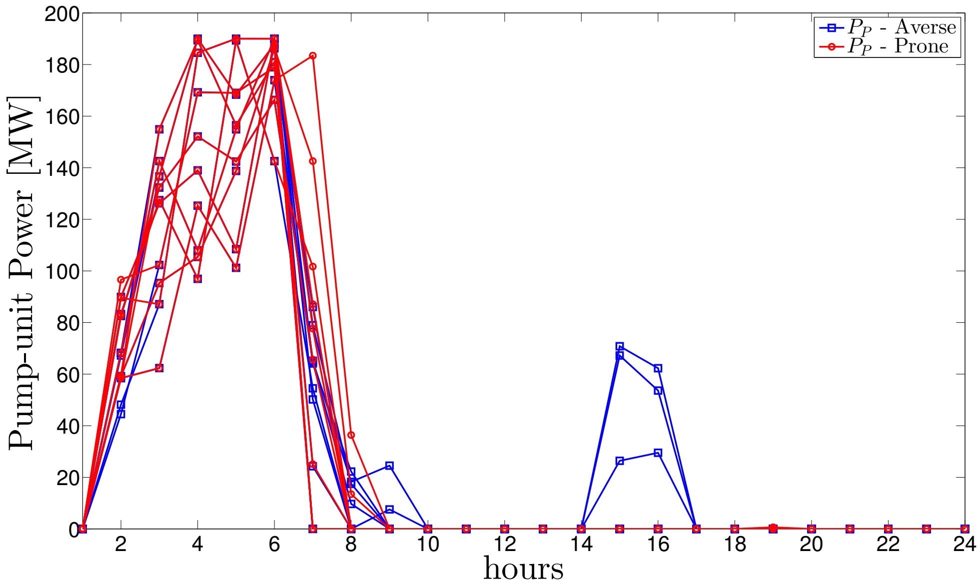

Figure 4.26: Pump-unit power: prone and averse attitude towards risk

The energy stored in the reservoir is a direct consequence of the pump-unit operation, therefore one can see, in Figure 4.27, the 3 scenarios mentioned before reaching the maximum reservoir's level at 17h.

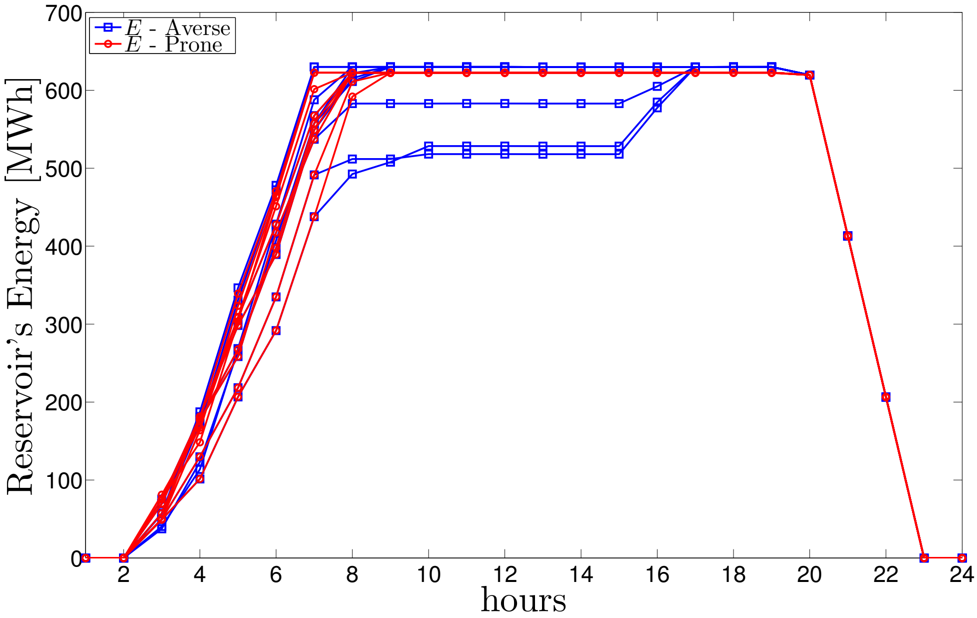

Figure 4.27: Energy stored in the reservoir - risk averse and risk prone

Figure 4.28 depicts the wind power directly delivered to the grid for both prone and averse decision makers.

The two strategies take different approaches when the positive imbalance is equal to the market price (1h - 18h). The prone to risk strategy chooses to define P_G as zero, thus avoiding regulation costs. The averse to risk strategy does not mind some minor regulation costs, in periods with small difference between p and p^-, in order to define a balanced value of P_G. This way, the consequences of the real wind power being close to the minimum or maximum wind power considered should be similar.

From 19h until the end of the day, when $p^- = p$, the averse strategy avoids all risk and defines P_G as the maximum available wind power in all scenarios considered. The P_G value defined by the decision make with a prone attitude towards risk is more aggressive, since it opens the possibility of regulation costs in order to improve the system's profitability.

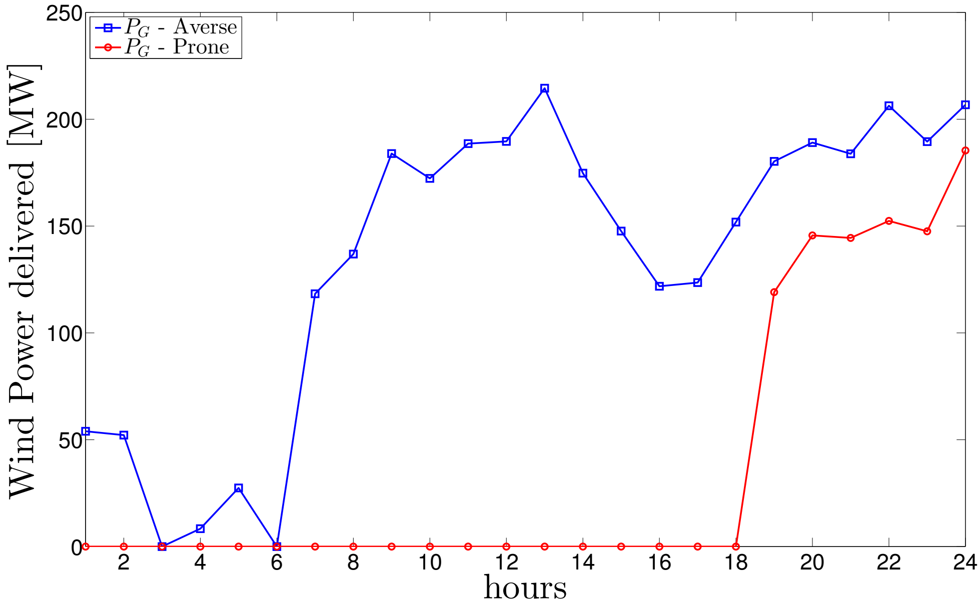

Figure 4.28: Wind power directly delivered to the grid - risk averse and risk prone

Figures 4.29 and 4.30 reflect the choices made by the DA optimization regarding the wind power directly delivered to the grid. It is possible to observe that the prone decision maker is more susceptible to positive imbalances and the averse to risk defines a strategy more receptive to negative imbalances.

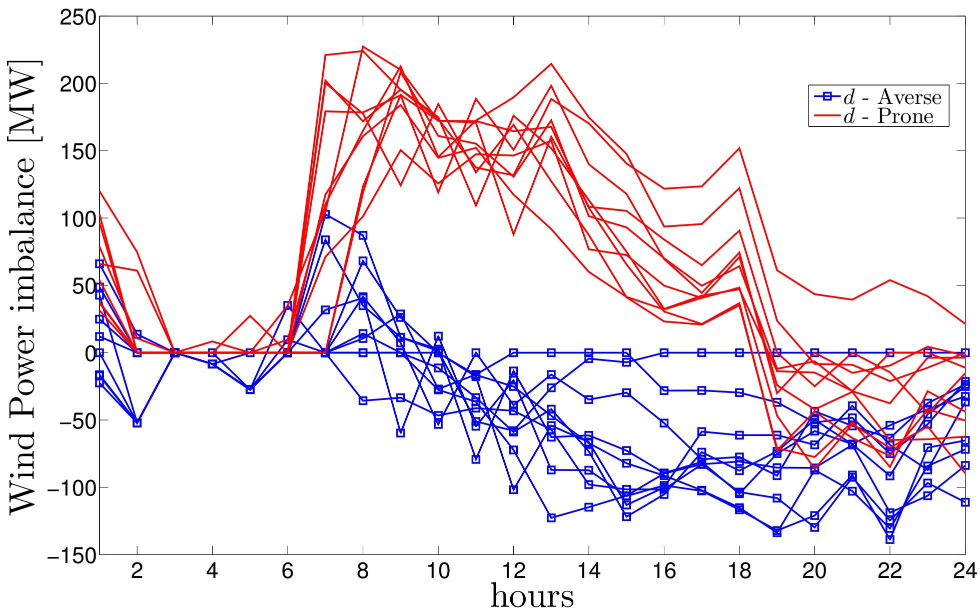

Figure 4.29: Wind power imbalances - risk averse and risk prone

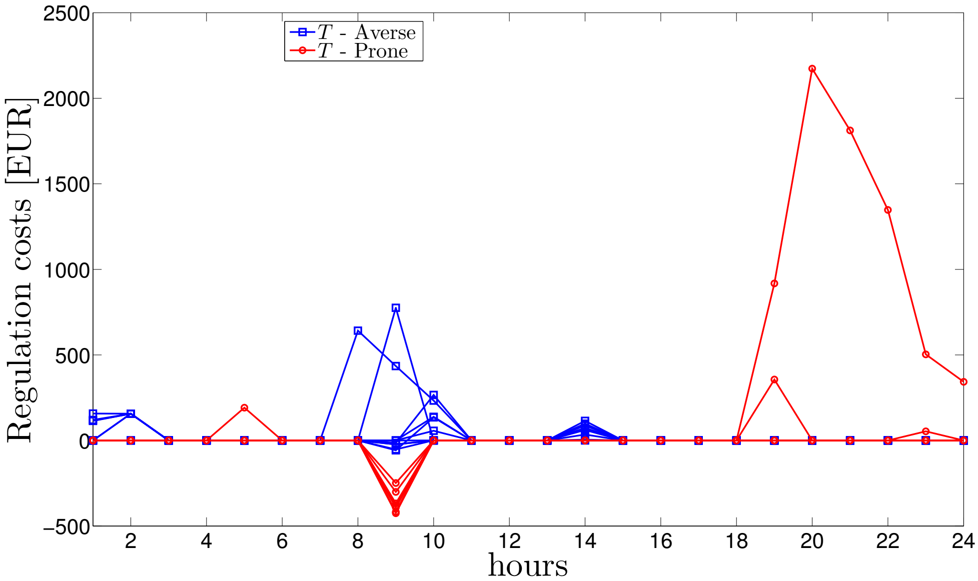

Figure 4.30: Regulation costs - risk averse and risk prone

4.2.5 Multi-attribute Utility Function - Multiple Decision Makers

The analysis of this section is focused on the waste of renewable energy (P_{DL}), therefore uses the multi-attribute utility function (Section 3.2.1) to evaluate the results of three decision makers with different attitudes towards the curtailment of wind energy.

In the MIBEL the market and imbalance prices can not be negative, so the delivering of wind power to the grid is always more profitable than to curtail it. In other electricity markets, such as the Dutch, German and Nordic [38] [39], a negative price regime is established, where imbalances and market prices can assume negative values. In this market conditions is economically disadvantageous to sell energy in those negative periods, hence the importance of P_{DL}. To comply with this conditions, it is assumed that the system has the capacity to waste wind power energy in a set of dumping loads.

Since the prices considered for this case-study do not account negative values, for the evaluation of the multi-attribute utility function the Nordic (ELSPOT) electricity market and imbalance prices presented in Figure 4.31 are used as input.

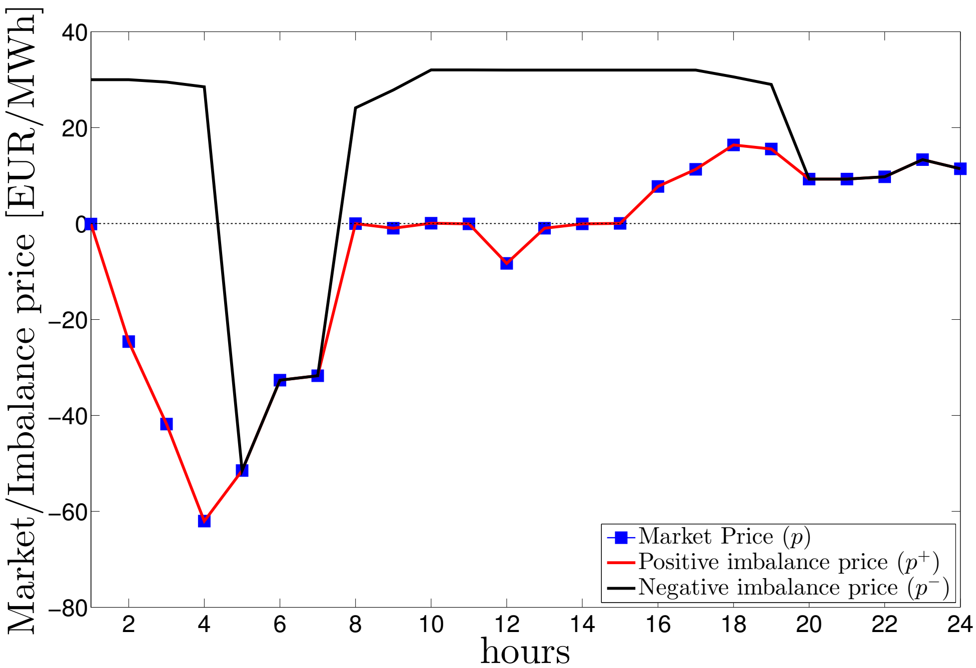

Figure 4.31: ELSPOT market and imbalance price considered

From 1h to 15h there are only two hours where is slightly more profitable to deliver energy than to waste it: 10h ($p_{10} = 0.07$ EUR/MWh) and 15h ($p_{15} = 0.03$ EUR/MWh). From 16h onwards the market price is positive.

Figure 4.32 depicts the wind power wasted in every scenario considering the expected value objective function of the day-ahead stochastic optimization. The algorithm only curtails wind power as a last resort, but, given the pump and storage unit limitations, it is forced to wasted considerable amounts of renewable power in order to avoid negative income.

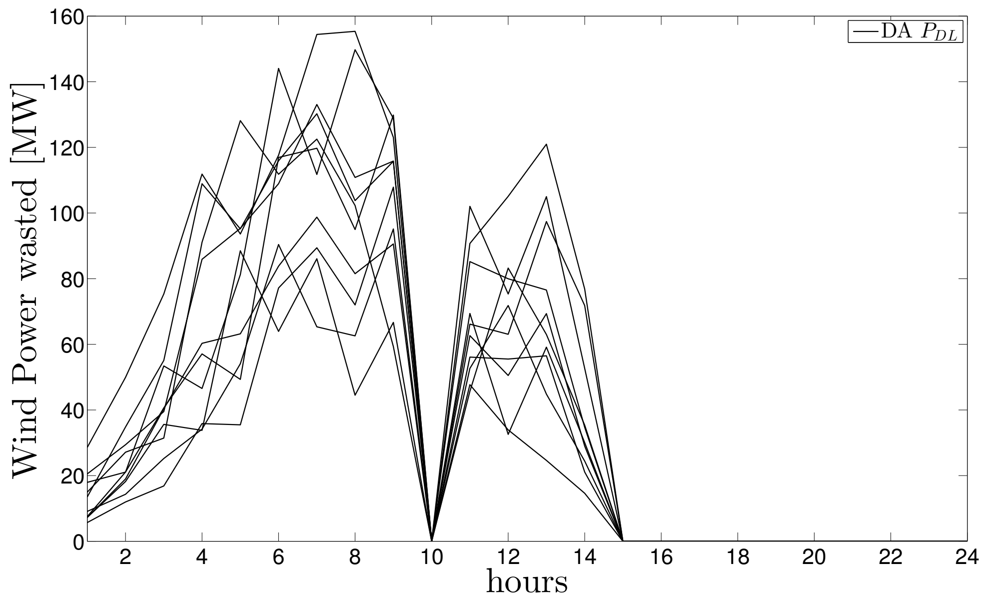

Figure 4.32: Wind power wasted - expected value objective function

To account for the social stigma that the wasting of renewable energy entails, the multi-attribute utility function allows the modelization of the decision maker's attitude towards this issue. For this case-study three decision makers with different trade-off and attitudes towards the curtailment of wind power were considered.

Table 4.3 represents the trade-off which characterises each decision maker, as explained in Section 3.2.1. Decision Maker A is the one that shows more willingness to suppress the wasting of wind energy, since will pay 200€ to decrease 1 MWh of wasted renewable energy, on the other hand, DM C is only predisposed to spend 67€ to decrease 1 MWh of P_{DL}.

The trade-off is represented in the utility function by the parameters k_1 and k_2 and the risk attitude is expressed by the coefficient β.

Table 4.3: Trade-off between profit and wind energy curtailed for each decision maker

	Trade-off
Decision Maker A	200 €/MWh
Decision Maker B	155 €/MWh
Decision Maker C	67 €/MWh

Figure 4.33 illustrates the average wind power wasted for each decision maker.Considering a strategy averse to the curtailment of wind energy, the stochastic DA multi-attribute utility function results in a solution without P_{DL} for every DM, despite the difference in the trade-off. With a strategy prone to waste wind energy, all three DM present P_{DL} at the first hours of the day.

As it was expected, from the analysis of Table 4.3, the decision maker that has a smaller value of P_{DL} is DM A, on the contrary, DM C has the biggest amount of renewable energy curtailed.

The comparison between the amount of renewable energy wasted considering the expected value objective function and the multi-attribute utility function reveals that even a decision maker with less willingness to avoid wind power curtailment has a significant reduction of P_{DL} in comparison with the expected value solution.

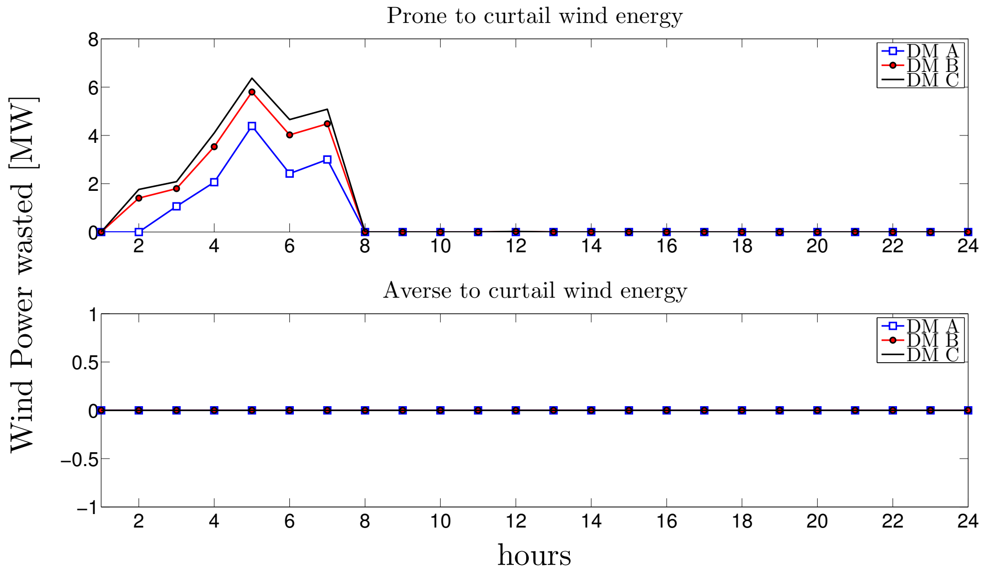

Figure 4.33: Wind power wasted for each scenario and decision maker

4.3 3 Months Analysis

This section aims to evaluate the efficiency of the DA stochastic algorithm at a large scale. Using 3 months of prices and wind power data is possible to obtain a reliable comparison between the use of stochastic forecasting and point forecasting.

To evaluate the performance of each objective function, comparatively with point forecasting, a γ coefficient is establish. As Equation 4.1 points out, this coefficient results from the difference between the point forecast profit and the function under evaluation, divided by the point forecast profit.

$$\gamma = \frac{\text{Profit}(PF) - \text{Profit}(Function)}{\text{Profit}(PF)} \cdot 100\% \tag{4.1}$$

A first analysis is made considering perfect knowledge of market and imbalances prices for the Iberian and Nordic electricity markets.

Tables 4.4 and 4.5 show the profit for the point forecast and wind power scenarios optimization, this last considering the expected value objective function and the unidimensional utility function with two decision makers: one averse and the other prone to risk. There is also presented the comparison between the deterministic and stochastic optimizations (γ).

Considering the Iberian market, the use of wind power scenarios results in a expected profit improvement of 0.65% comparatively with point forecasting. The unidimensional utility function results show that is expected that a prone to risk decision maker will obtain a bigger profit than an averse.

With ELSPOT prices the use of stochastic representations to account for wind power uncertainty also displays as an advantageous choice, with a 1.14% increase in profit comparatively with the deterministic approach. In this market conditions the averse to risk attitude shows a negative γ, while the decision maker with a prone to risk attitude shows improvement towards point forecast approach.

Table 4.4: Results considering MIBEL prices with perfect forecasting

	Point Forecast	Wind Power Scenarios		
		Expected Value	Averse utility Function	Prone Utility Function
Profit	8,361,800 €	8,416,200 €	8,388,600 €	8,393,800 €
γ	n.a.	0.65%	0.32%	0.38%

Table 4.5: Results considering ELSPOT prices with perfect forecasting

	Point Forecast	Wind Power Scenarios		
		Expected Value	Averse utility Function	Prone Utility Function
Profit	8,776,800 €	8,876,700 €	8,718,600 €	8,854,800 €
γ	n.a.	1.14%	−0.66%	0.89%

As mentioned before the stochastic DA optimization chooses extreme positions to take full advantage of the periods where there are no regulation costs. Although this is the optimal solution with perfect knowledge of market and price imbalances, in a real situation an inaccurate imbalance prediction could lead to considerable regulation costs, thus affecting the system's profit. To simulate this situation a naïve model is used in order to establish the imbalance prices to be considered as input in the stochastic day-ahead optimization.

The naïve model uses real market prices, but the negative and positive imbalance prices are defined as margins with a predefined and constant distance towards the market price. For the positive imbalance, the distance is defined as the average value of $\frac{p^+}{p}$ and for the negative imbalance as the average of $\frac{p^-}{p}$. Those values were calculated considering the 3 months of data available. Table 4.6 indicates the parameters used in the naïve model.

Table 4.6: Parameters used in the naïve model - MIBEL and ELSPOT

Electricity Market	Market Price	Positive Imbalance	Negative Imbalance
MIBEL	p	$p \cdot 0.8$	$p \cdot 1.05$
ELSPOT	p	$p \cdot 0.87$	$p \cdot 1.09$

Figure 4.34 depicts an example of the imbalance prices obtained with the naïve model for the Iberian electricity market. With this model market and imbalance prices never cross, hence there are always regulation costs associated with power imbalances.

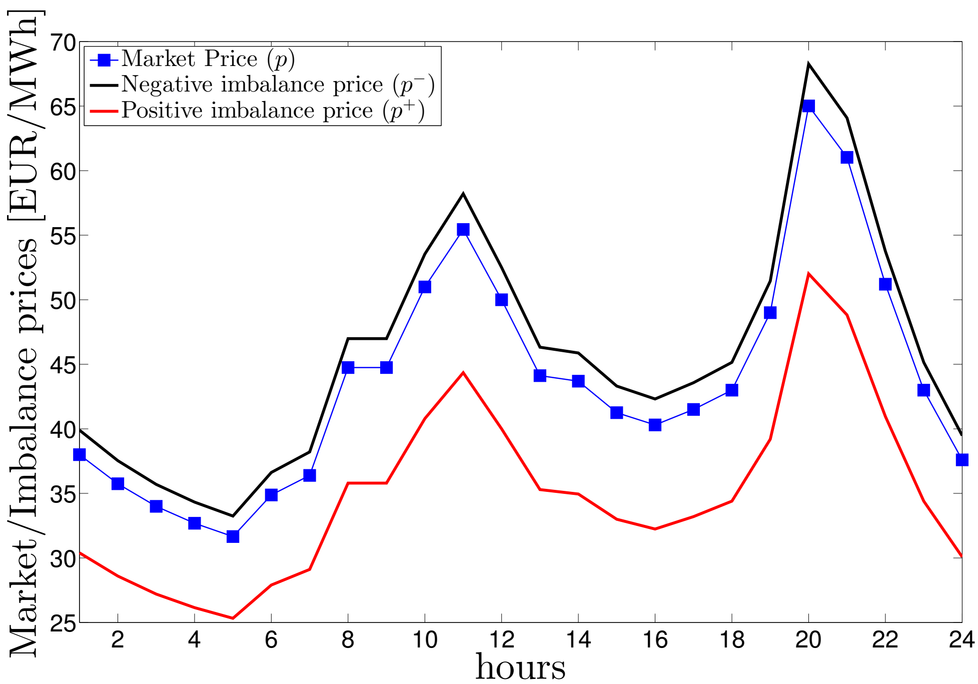

Figure 4.34: Market and imbalance prices with the naïve model

Tables 4.7 and 4.8 show the profit for the Iberian and Nordic electricity markets, considering the naïve model.

With MIBEL prices the stochastic optimization maintains its advantage towards the deterministic approach, but with a less γ, with the model it is only 0.40% better than the point forecast. Using the unidimensional utility function becomes uninteresting, since both decision makers obtain less profit than P.F..

Table 4.7: Results considering MIBEL prices with the naïve model

	Point Forecast	Wind Power Scenarios		
		Expected Value	Averse utility Function	Prone Utility Function
Profit γ	8,361,800 € n.a.	8,394,700 € 0.40%	8,245,300 € -1.39%	8,360,200 € -0.02%

Representing imbalance prices as margins of the market price affects the dynamic of the Nordic electricity market, since negative prices cease to exist and the imbalance prices follow a less variable pattern. This affects the efficiency of the naïve model and leads to a substantial decrease in profit for all objective functions that considered wind power scenarios as input. With the naïve model the profit obtained using the expected value declines in 135,000 €, which represents a decrease of 1.54% in terms of γ.

Table 4.8: Results considering ELSPOT prices with the naïve model

	Point Forecast	Wind Power Scenarios		
		Expected Value	Averse utility Function	Prone Utility Function
Profit	8,776,800 €	8,741,700 €	8,545,200 €	8,737,200 €
γ	n.a.	−0.40%	−2.64%	−0.45%

Considering the Iberian market, the negative imbalance is, in average, only 5% more than the market price, which is still very close to the market price, thus leading to small regulation costs and, consequently, could lead to extreme bids from the day-ahead optimization. To evaluate this possibility a naïve model (v2) was used, in which both positive and negative imbalance prices have a margin that constitute $\pm 20\%$ of p. The results shown in Table 4.9, reveal the importance of the correct prediction of negative imbalances. With the consideration of more strict imbalance prices in the algorithm all stochastic objective functions saw their profit improve, with the expected value registering an improvement on the point forecast of 1.08%.

Table 4.9: Results considering MIBEL prices with the naïve model (v2)

	Point Forecast	Wind Power Scenarios		
		Expected Value	Averse utility Function	Prone Utility Function
Profit	8,361,800 €	8,452,400 €	8,293,600 €	8,428,000 €
γ	n.a.	1.08%	−0.81%	0.80%

Chapter 5

Conclusions and Future Work

This chapter is divided into two sections, the first summarizes the principal findings and conclusions drawn from the results presented in Chapter 4 and the last describes a few recommendations and directions in order to improve and continue the work done in this dissertation.

5.1 Conclusions

This section discusses the conclusions obtained from the analysis of 3 months of wind and prices data. Table 5.1 summarizes the stochastic optimization improvement over point forecasting, using the γ parameter (defined in Section 4.3) for the comparison.

Considering the expected value objective function, with perfect price forecasting the analysis shows better results than point forecasting, with $\gamma = 0.65\%$ for MIBEL prices and $\gamma = 1.14\%$ with prices from the Nordic electricity market. The introduction of the naïve model adds errors to the imbalance prices forecasts, considered as input in stochastic day-ahead optimization, and results in a expected revenue smaller in comparison with the perfect price forecasting. With ELSPOT prices, the naïve model not only lessens the profit compared with the perfect forecasting, but also shows worse results than the deterministic approach. The introduction of naïve model (v2) aims to equalize the margins of both positive and negative imbalance prices, thus increasing the impact of regulation costs. This new model was only applied to the MIBEL since the first version of the naïve model proved to be inefficient for ELSPOT. Results show an improvement in the expected value of the system regarding the first naïve model and the point forecasting method.

Table 5.1: Stochastic optimization improvement over point forecasting

	Wind Power Scenarios		
	Expected Value	Utility Function - Averse	Utility Function - Prone
Perfect Price Forecasting - MIBEL	0.65%	0.32%	0.38%
Perfect Price Forecasting - ELSPOT	1.14%	−0.66%	0.89%
Naïve model - MIBEL	0.40%	−1.39%	−0.02%
Naïve model - ELSPOT	−0.40%	−2.64%	−0.45%
Naïve model (v2) - MIBEL	1.08%	−0.81%	0.80%

A comparison between the expected value objective function and the utility function reveals that for, all cases studied, the expected value results in more profit than the prone and adverse decision makers.

Since the aim of the unidimensional utility function is to consider the decision makers attitude towards risk, is incorrect to evaluate its performance based solely on the total profit of the system.

Table 5.2 shows the profit and regulation costs for both decision makers when MIBEL prices with perfect price forecasting are used as input. The averse to risk DM achieves 5200€ (−0.06%) less profit than the prone to risk, which is insignificant considering the order of magnitude of the profit. On the other hand, the regulation costs paid by the prone to risk decision maker are 75.5% more than its averse homologous (+10,132€).

Table 5.2: Regulation costs and profit for the unidimensional utility function - MIBEL perfect price forecasting

	Utility Function - Averse	Utility Function - Prone
Profit	8,388,600 €	13,425 €
Regulation Costs	8,393,800 €	23,557 €

The perfect knowledge of market and price imbalances does not guarantee the best expected profit from the optimization, since the algorithm takes advantage of the periods without regulation costs to extreme its bids to the electricity market, which results in a sub-optimal real operation, as explained in Chapter 3. The naïve model (v2) improvement over perfect knowledge of price proves the situation described above. On the other hand, the decline in profit considering the same naïve model but with ELSPOT prices enhances the importance of choosing an adequate forecast model to predict the imbalance prices used as input in the day-ahead stochastic optimization.

The analysis and results presented in this dissertation reveal the importance and efficiency of the operational management strategy. Despite the uncertainty associated with wind power forecasting the algorithm is able to reduce regulation costs to a minimum value.

Although with the best case studied (MIBEL with naïve model (v2)) an improvement of 1.08% in the expected profit over point forecast is obtained, the outcome reveals only more 90,600 € in 3 months of operation.

Since one of the main objectives of this dissertation is to evaluate the use of a pump-hydro storage unit to suppress power imbalances occurring due to wind power uncertainty, considering the formulation of chapter 3 and the case studies from chapter 4, one can conclude that the amount of regulation costs avoided might not justify the investment in storage technology solely for compensating the imbalances.

5.2 Future Work

For future works there are some recommendations that have potential to improve the results obtained.

- The development of a probabilist forecast model to predict the imbalance prices and direction for the day-ahead, in order to overcome the results obtained with naïve model (v2);

- The reservoir's energy level (E) at the end of the optimization period could be set to a less restrict value. Either by defining a minimum and maximum level at the end of the day or by defining weekly or monthly levels. This last solution requires a continuous optimization, but would eliminate those situations where the operational management strategy is forced to pay regulation costs for the surplus of energy generated in order to empty the reservoir.

- Reformulate the day-ahead optimization problem in order to consider the hydroelectric power (P_H) and the wind power directly delivered to the grid (P_G) as scenario-dependent variables. This way, the algorithm will be able to suppress individual negative imbalances by operating the hydro unit. At the end of the optimization a single bid for each hour has to be present to the electricity market, therefore there is the need to create an additional variable, which has to be global, to represent the bid. For all scenarios a new constraint must be create, to guarantee that the bid is feasible for all scenarios considered.

- In this dissertation the operational management strategy aims to minimize the absolute value of the power imbalances. Therefore, even if there are no penalization for negative imbalances the algorithm will use the energy stored in the reservoir to suppress the deficit. The water stored in the reservoir is the same used for price arbitrage, so the avoidance of an imbalance in hours with no regulation costs could be more disadvantageous than helpful, since it could spend the water needed to fulfil the bid at later hours incurring in regulation costs and/or less gross revenue. My recommendation is to use a forecasting method to predict imbalance prices and use them as inputs for the strategic management strategy.

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